PHD

Firm-Level Risk and Systemic Risk Analysis in the Insurance Sector during the Subprime Mortgage Crisis: CDS VS. Non-CDS-Based Risk Indictors

Gao, Hui

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FIRM-LEVEL RISK AND SYSTEMIC RISK ANALYSIS IN THE INSURANCE SECTOR DURING THE SUBPRIME MORTGAGE CRISIS: CDS VS. NON-CDS-BASED RISK INDICATORS

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Hui Gao

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Abstract

Although extensive literature has investigated the systemic relevance of the insurance sector during the financial crisis of 2007-2009, mixed results have been presented. This thesis considers firm-level risk assessments in contrast to systemic risk evaluations to examine whether insurers are riskier than banks and non-financial institutions (NFIs). The role of CDS data in capturing risks has been compared with that of non-CDS data as well in this research. By applying CDS and non-CDS data of worldwide banks, insurers and NFIs into the two groups of risk methodologies, this thesis shows that insurers contribute more to and are affected more by credit risk than the other two sectors. This study also finds that credit risk links among companies are stronger than other types of risk connections. What' more, CDS provides earlier risk warning signals than non-CDS information. In addition, firm-level risk has relatively weak non-linear correlation with systemic risk, i.e. firm risk is not able to reflect some information that is only contained in systemic risk. Finally, the systemic vulnerability analysis of distress dependence matrix (DiDe SV) and SRISK, involving both equity and balance sheet information, are superior to any other risk measures adopted in this thesis in terms of its predictive ability of the subprime mortgage crisis.

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1 Introduction

Since the subprime mortgage crisis, activities of non-bank financial institutions (NBFIs) have raised many concerns among practitioners, regulators and academics. By conducting non-core or banking activities, NBFIs have become intensively interrelated with banks and other institutions. Without appropriate regulations on them, nevertheless, NBFIs are associated with high potential risk. The 2007-2009 financial crash is characterised by NBFI collapses and systemic risk, which triggered extensive defaults of financial and non-financial institutions, and finally resulted in the turbulence of the global financial market. Systemic risk is another hot topic after the crisis, however there is still no consensus on its definition yet. This thesis follows Financial Stability Board (FSB) and defines systemic risk as "a risk of disruption to financial services that is caused by an impairment of all or parts of the financial system and has the potential to have serious negative consequences for the real economy." Traditionally, systemic risk is believed to be associated with banks. However, the subprime mortgage crisis reveals that NBFIs are systemic relevant as well. Particularly, the insurance sector, classified as NBFIs, has attracted increasing attention from both academics and regulators as a result of the famous insurer failures in the last financial crash such as American International Group (AIG), Municipal Bond Insurance Association (MBIA) and the AMBAC Financial Group.

In the 2007 financial meltdown, Credit Default Swap (CDS) market is considered to play an essential role in spreading risk. CDS transactions were most prevalent among NBFIs and its trading volume peaked in the historical high prior to the turbulence. However, the self-reflexive characteristics[1] of CDS spreads, and the lack of transparency in the CDS market bred systemic risk. Considering the contributions of the CDS market to systemic risk, and the well-known failures of the CDS issuers in the subprime mortgage crisis, this thesis tries to exploit the role of CDS information in risk analyses. The popularity of the CDS transactions is attributed to the activities of some insurance companies, which were the main net sellers of CDS protections prior to the financial meltdown. (ECB, 2009) Particularly, AIG, which was highly leveraged with heavy holdings of the U.S. mortgage portfolios, collateralised debt obligations (CDOs) and collateralised loan obligations (CLOs), issued substantial CDS contracts that protect housing related assets. While the bubble in the subprime mortgage market burst, AIG was required to meet the cash collateral calls on its CDS trades. Further claims were triggered afterwards when AIG's credit rating was downgraded. Consequently, AIG was bankrupt and

[1] Elaborated in Section 2.4.3

led to the domino effect in the financial market.

This section consists of the following subsections: Section 1.1 presents relevant evidences of the 2007-2009 financial crisis. Section 1.2 specifies motivations and contributions of this thesis. Section 1.3 lists research questions. Section 1.4 summarises methodologies and data used in this research. Section 1.5 shows empirical findings and Section 1.6 demonstrates the structure of the thesis.

1.1 Evidence of the 2007-2009 Financial Crisis

The 2007-2009 financial crisis was triggered by the US subprime mortgage crisis at the beginning and finally led to global financial market collapse and worldwide economic downturn. During that time, we witnessed huge losses in investor confidence and securities values, which resulted in institution failures. GDP decline and unemployment rate rise simultaneously reached new peaks since the 1930s Great Depression. Unprecedented expansions of fiscal and monetary policies, and substantial bailouts of financial institutions were carried out by multinational governments and central banks. Although originated in the US, the crisis quickly spread abroad, giving rise to the subsequent European Sovereign-Debt Crisis.

It is well known that the 2007 financial meltdown was caused when the bubble burst in the subprime housing market in US. It is a process of the boom and bust cycle. Credit intermediation, especially through non-bank financial institutions (NBFIs) and the off-balance sheet activities of banks that were not properly regulated, boosted the economic prosperity and financial efficiency. However, in the credit booming and the building up of asset bubbles, risk is transferred and expanded through the intensifying connections between market participants. As soon as one institution defaults, others will be affected considerably. Systemic event occurs due to the extensive defaults of financial institutions and the credit crunch in the financial system. The 2007-2009 financial crisis is a representative systemic crisis.

Financial derivatives, especially Credit Default Swap (CDS) contracts, facilitated the risk amplification during the 2007 financial crash. The housing bubble prior to the crisis was funded from Mortgage-Backed Securities (MBS) and Collateralized Debt Obligations (CDOs), with the latter one being the main reference asset that is insured by CDS contract. When the subprime mortgage market was collapsed, the relevant derivative markets particularly the CDS market was disrupted. CDS transactions achieved the historical high prior to the subprime mortgage crisis and were believed to be responsible for the occurrence of systemic risk. Considering as well the NBFI failures such as AIG, MBIA and AMBAC that were active in CDS trading, this thesis pays attention to the role and characteristics of CDS.

The remainder of Section 1.1 is structured as follows: Section 1.1.1 demonstrates activities of NBFIs during the 2007 financial crisis. Section 1.1.2 specifies activities of insurers during the 2007 distress. Section 1.1.3 reviews theories of systemic risk. Section 1.1.4 illustrates CDS and CDS market.

1.1.1 Non-Bank Financial Institutions in the 2007-2009 Financial Crisis

All types of financial institutions have extensively strengthened their interconnections in the last two decades. They have blurred their business boundaries by moving to non-core activities, and thus link and compete with each other. For instance, Billio et al. (2011) state that banks and insurers supply funds to hedge funds but at the same time they conduct their own trading activities that compete directly with hedge funds. The Geneva Association (2010) also gives an example that insurers began to get involved in derivatives trading, credit default swap issuance, and investment management, which competed with banks, hedge funds and brokers/dealers. The most important business model change that contributed to the 2007 financial crisis would be NBFIs as credit intermediaries conducting bank-like financial activities.

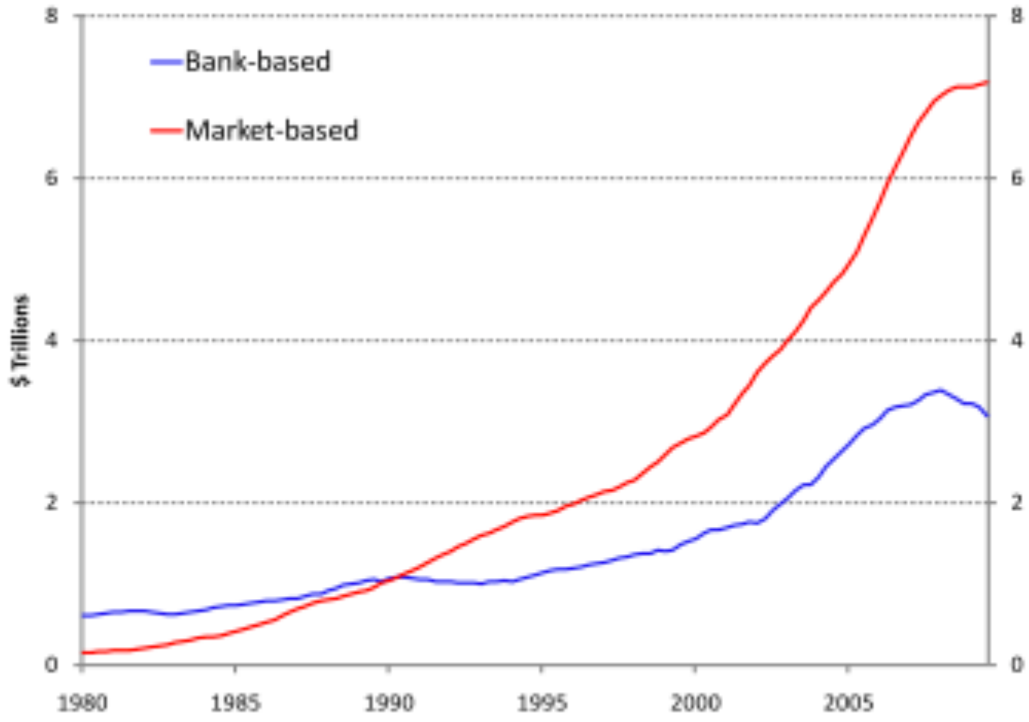
(1) Credit Intermediation

Credit intermediation occurs when savers deposit their savings to banks, which then use the funds to provide credit to borrowers. On one hand, credit intermediation provides credit and liquidity to economy. Compared with direct lending between lenders and borrowers, credit intermediation reduces monitoring costs and diversifies portfolio investments. (see Pozsar, Adrian, Ashcraft, and Boesky, 2010) On the other hand, however, banks are faced with credit risk and liquidity risk as they take short-term deposits and lend the funds in the form of long-term loans, also called maturity transformation. Credit risk refers to the risk of default in the loan lending, while the liquidity risk refers to the mismatch of the short-term funding and long-term lending (see The Geneva Association, 2010). Therefore, most of the historical crises stemmed from banks that are then under rigorous supervision.

(2) Structure of NBFIs Credit Intermediation

Traditionally banks are credit intermediaries, however according to Financial Crisis Inquiry Commission (2010), NBFIs have become active in banking business due to the following reasons: (1) NBFIs was to meet the credit demand in market as a result of strict restrictions on banks; (2) banks started off-balance sheet activities through NBFIs due to capital regulations; (3) there was much less supervision on NBFIs from the regulators. Adrian and Shin (2010) have shown the home mortgage holdings between bank-based intermediation and market-based intermediation from 1980 to 2009 as shown in **Error! Reference source not found.**. In their work, bank-based holdings involve commercial banks, savings institutions, and credit unions.

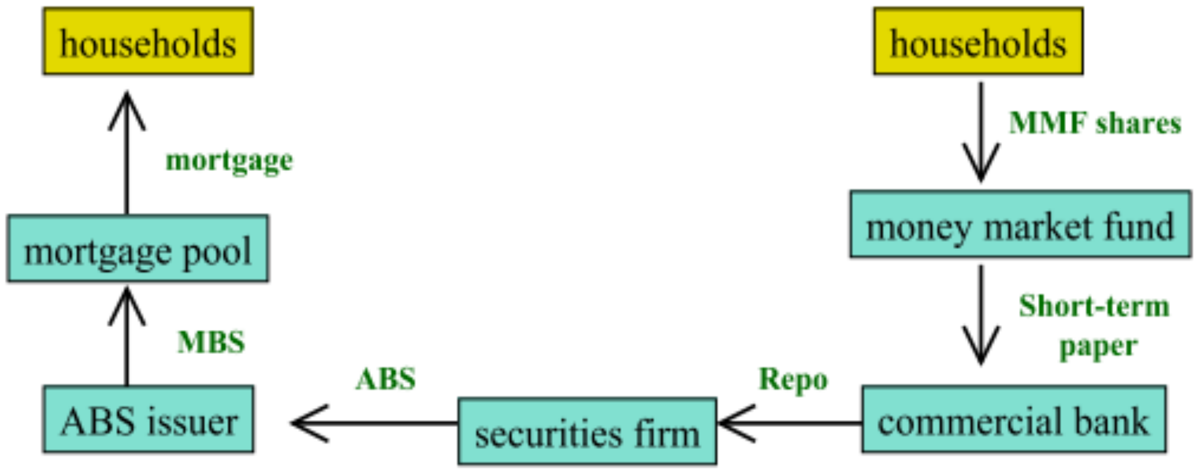
Market-based holdings incorporate government-sponsored enterprise (GSE), GSE mortgage pools, private mortgage pools and asset-backed securities (ABS) issuers. In **Error! Reference source not found.**, market-based holdings exceeded bank-based holdings from about 1990 and remained the domination until 2009.



Source: Adrian and Shin (2010)

Figure 1 Market-Based and Bank-Based Holding of Home Mortgages, 1980 to 2009
The figure shows the holding level of bank-based intermediation compared with that of the market-based intermediation from 1980 to 2009. Bank-based holdings consist of commercial banks, savings institutions, and credit unions. Market-based holdings include government-sponsored enterprise (GSE), GSE mortgage pools, private mortgage pools and asset-backed securities (ABS) issuers.

Adrian and Shin (2010) have summarised one possible chain of market-based financial intermediation as shown in **Error! Reference source not found.**: mortgage originators such as banks expand mortgage loans to subprime borrowers and sell the loans to a mortgage pool that is financed by issuing mortgage-backed securities (MBS). MBS is then classified into different tranches of collateralized debt obligations (CDOs) by an asset-backed securities (ABS) issuer. A securities firm, such as an investment bank, is the potential holder of CDOs and finances its position from repurchase agreements (repos) with a commercial bank. Safer tranches of CDOs are insured by credit default swap (CDS) contracts, which are issued mainly by insurers. The commercial bank then obtains liquidity by issuing financial commercial paper (CP) to money mareket fund (MMF), which finally raises funds from selling MMF shares to households.



Source: Adrian and Shin (2010)

Figure 2 Intermediation Chain in a Market-Based Financial System
The figure shows a possible intermediation chain in a market-based financial system, which starts with lending from ultimate creditors (households) and ends with credit flowing to ultimate debtors (households).

(3) Risk of Credit Intermediation in NBFI System
In addition to the risks of banks as credit intermediaries, which is mentioned in Section 2.1.1, NBFIs are associated with extra risks when get involved in credit intermediation. This is supported by Pozsar et al. (2012) who focus on the level of guarantees for credit intermediation in banking system and in NBFI system. They demonstrate that a third party could provide credit and liquidity guarantees to enhance credit intermediation. Particularly if credit intermediation is guaranteed by the public sector, it is called the official enhancement. Pozsar et al. (2012) have analysed the pre-crisis degree of official enhancements among depository institutions (including commercial banks) and NBFIs. They show that credit intermediation activities in depository institutions are more or less enhanced, however those activities of NBFIs are not enhanced at all. Credit intermediation activities of NBFIS include CDS issuance, securities lending and financial guarantees from insurers, and term ABS and bi-lateral repos from finance companies. This could explain the higher risk of credit intermediation in NBFI system than that in banking system. The Financial Crisis Inquiry Commission (2010) also asserts that bank-like NBFIs are more prone to triggering financial instability than banks in that NBFIs employ high leverage, rely on short-term funding markets and have no access to explicit government supports[2] for banks. There is also no regulatory framework governing and monitoring the activities of NBFIs involved in high-risk transactions.

[2] Such as deposit insurance and the lender of last resort that reduce the liquidity risk of banks

(4) NBFI Failures in the 2007-2009 Financial Crisis

This section demonstrates a list of events that represent a partial picture of the 2007 - 2009 financial meltdown, with particular emphasis on NBFI activities. According to the staff report of the Financial Crisis Inquiry Commission (2010), NBFI failures in the 2007-2009 financial crisis experienced a few stages:

Liquidity crisis of 2007 – Subprime mortgage lenders, obtaining funding from the securitisation market, were the first victims. Two hedge funds of Bear Stearns and two investment funds of BNP Paribas collapsed due to their considerable losses in housing related assets. Meanwhile, commercial paper market and money market were hit hard because of the disruptions of MBS and CDOs. Northern Rock, a British bank, failed to finance from money market, and consequently requested loan facility support from the Bank of England.

The run on Bear Stearns in early 2008 – Financial guarantors who provide credit guarantees on subprime mortgage assets were faced with payment obligations and were downgraded since the collapse of the housing market. Following that, bondholders were in a panic to liquidate auction-rate securities (ARS), questioning the ability of financial guarantors to continue guaranteeing the municipal bonds they were holding. Bear Sterns went bankrupt in March 2008 because of its numerous losses in mortgage-related investments and its failure to raise funds from repo market.

The panic of 2008 – Lehman Brothers was disrupted due to its heavy holdings of housing-related assets and failed in financing its debt via the frozen capital market such as repo market. The failure of Lehman Brothers in September 2008 was the final trigger of the crisis.

1.1.2 Insurers in the 2007-2009 Financial Crisis

As a subsector of NBFIs, insurance companies are believed to play a prominent role in posing a risk to financial market during the subprime mortgage crisis, especially considering the famous failures of American International Group (AIG), Municipal Bond Insurance Association (MBIA) and AMBAC Financial Group. A brief description of insurers' activities and the crisis aftermaths on them are demonstrated in this section.

The traditional main role of insurance companies is to provide protection by accepting risks from policyholders, from whom insurers collect premium payments (The Geneva Association (2010)). Although insurers assume risk, they manage it, diversify it, and transfer portion of it to reinsurers. Furthermore, insurance risk is idiosyncratic, unlike banking activities that are associated with credit risk and liquidity risk, which incline to relate to economic cycle. The premiums raised by insurance companies would be used to support capital market and finance economy. Since claims on the insurance payments usually won't be triggered until long time after premiums have been taken, insurers are able to take long-run investment, which provides long-term capital to companies. Given the aforementioned features, insurance is one of the most important sectors in financial market. In 2008, the global premium volume in insurance was about USD 4.4 trillion, which accounts for 7.3 per cent of the worldwide GDP. Regarding the size of assets managed by insurers in 2008, it was USD 18.7 trillion that constitutes about 11 per cent of the worldwide total financial assets. However, like the case of all other NBFIs, the business areas of insurance companies have changed over the past years, extending towards non-traditional insurance and non-insurance activities as summarised by Muller et al. (2012) in Table 1.

Table 1 Activities of Insurance Companies

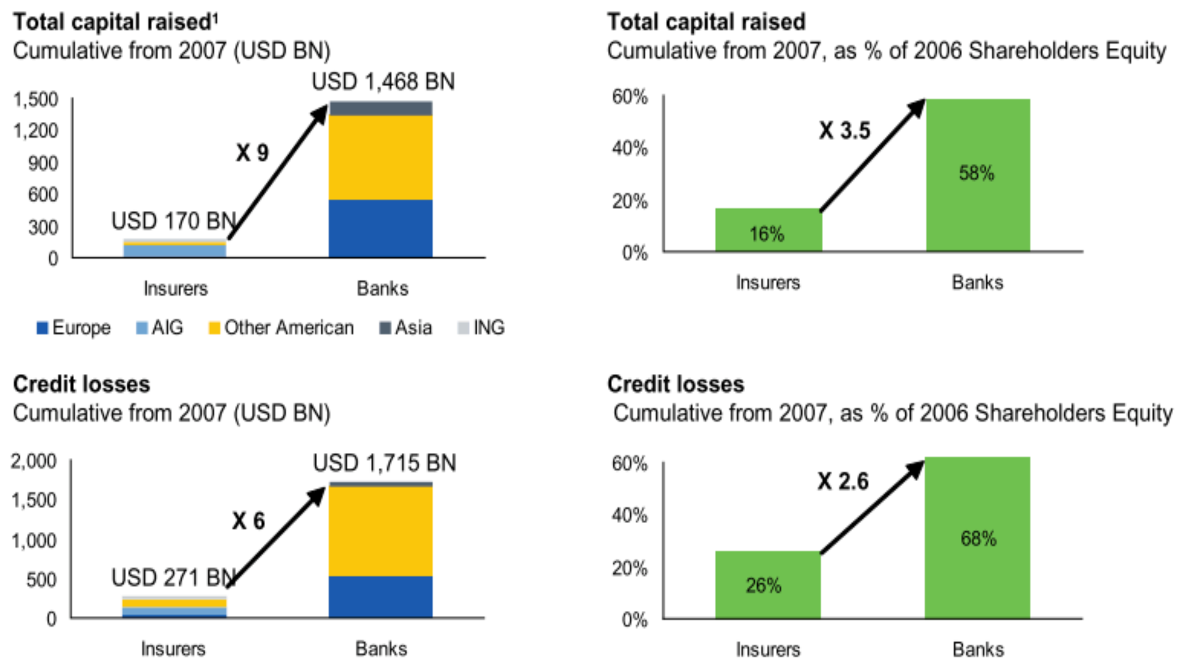
		Traditional ⟷ Non-t		
Insurance	Underwriting	Most life and non-life insurance business lines	Life insurance and variable annuities Mortgage guarantee insurance Trade credit insurance	Alternative risk transfer (e.g., insurance-linked securities) Financial guarantee insurance Finite reinsurance
	Invests and funding	Proprietary investment function (ALM[3]) Hedging for ALM proposes Funding through equity and debt issues, also securities lending	Proprietary and derivatives trading (non-ALM) Property management (related to investment portfolio)	Purely synthetic investment portfolios Cascades of repos and securities lending Scope and scale of activities beyond insurance remit
Non-insurance	CDS/CDO underwriting Capital market business Banking, including investment banking and hedge fund activities Third-party asset management Industrial activities			

Source: Muller et al. (2012)

The Geneva Association (2010) has compared the cumulative amount of total capital raised and credit losses of banks with those of insurers during the 2007 financial crisis as illustrated in **Error! Reference source not found.**. According to **Error! Reference source not found.**, gaps between banks and insurers indicated by the relative values of recapitalisation and credit losses that are computed as percentages of 2006 shareholders equity, are smaller than those

[3] Asset Liability Management, a practice of managing the risks resulting from the mismatches of assets and liabilities.

signified by the absolute values of recapitalisation and credit losses. However no matter on absolute basis or relative basis, insurers had less capital raised and less credit losses than banks. Baluch et al. (2011) also note that although there has been an increase in correlation between stock returns of banking and insurance, banks performed much worse than insurers with greater losses in equity values during the crisis.



Source: The Geneva Association (2010)

Figure 3 Recapitalisation and Credit Losses in Banks and Insurers
The figure shows the cumulative total capital raised and credit losses of banks and insurers in the crisis on both absolute and relative bases. Total capital raised refers to equity and preferred share capital raised from states and the capital markets, but not incorporates asset relief or lending by states.

The crisis effects on insurance companies are summarised by The Geneva Association (2010) according to the type of insurers:

Insurers with none or limited banking operations – Insurers with limited banking business are generally referred to "pure" insurance companies, which typically include life, non-life and composite insurers (e.g., Lincoln, Yamato Life, AEGON, The Hartford, etc.). These companies were only associated with limited losses during the financial collapse. They were affected due to exposures to financial instruments, connections with defaulted banks, liquidity problems, and the effects from the general economic recession. Generally, this type of insurers, especially life insurers, had less exposure than banks to structured products (e.g., CDS) because of their strict restrictions and regulations.

Bank/insurance conglomerates – Bank/insurance conglomerates such as BNP Paribas, HSBC and Credit Agricole with strong liquid holdings and low exposures to structured products remained unharmed from the 2007-2009 financial crash. However, some bank/insurance conglomerates such as ING suffered huge losses relative to the pure insurers. The failure of ING was mainly caused by its banking activities and its acquisition of a U.S. thrift. As a result of this acquisition, ING had to be under the regulations of the Office of Thrift Supervision (OTS) and thus more than half of its assets were required to transfer to mortgage-related investments. To meet the requirement, ING invested in abundant MBS, and incurred a huge loss in its portfolio holdings in 2008.

Insurers with wholesale banking operations – A typical example of this type of insurer is the American International Group (AIG), which was declared bankrupt during the 2007 financial meltdown. The difficulties did not stem from its insurance business but from its Financial Products division (AIG FP). The AIG holding company was subject to the US office of Thrift Supervision (OTS), as was AIG FP. However, AIG FP was domiciled in London. By using regulatory arbitrage, AIG FP operated outside of the control of both U.K. Financial Services Authority (FSA) and OTS. AIG FP was with high leveraged positions and was holding a large number of derivatives that involve mortgage-associated assets, CDOs and collateralised loan obligations (CLOs). Particularly, AIG FP guaranteed a high proportion of CDS contracts that provide guarantees on housing-related assets. After the downgrades of the subprime assets in 2007, AIG was required to meet the cash collateral calls on its CDS contracts and in September 2008, more cash collateral calls were demanded on AIG's CDS contracts when AIG's credit rating was downgraded. Faced with liquidity risk, AIG was bailed out by the U.S. Treasury eventually.

Monoliners – Compared with traditional insurers, monoliners (e.g., AMBAC, MBIA, FSA) mainly focus on providing financial guarantees and take credit risk, through which they cut down the borrowing cost of U.S. municipalities. Potential risks existed because monoliners increasingly offered financial guarantees on CDS contracts backed by AAA rated CDO and MBS, which were all undiversified and highly leveraged portfolios (CDS backed by MBS calls for lower capital coverage than a municipal bond). However, financial guarantees associated with CDS are heavily dependent on credit ratings. When the subprime mortgage crisis was triggered, credit ratings of the related CDS contracts were downgraded as well as the ratings of the monoliners, which, in turn, affected their counterparties. Similarly, mark-to-market losses, confidence crisis and liquidity risk contributed to the collapses of monoliners such as AMBAC and MBIA during the financial crash.

To summarise, the aforementioned studies suggest that it is insurers' non-core activities that are associated with systemic risk and financial crisis. AIG, MBIA and AMBAC collapsed during the subprime mortgage crisis in that they were more or less engaging in non-traditional business. According to The Geneva Association (2010), AIG itself represents 58 per cent of the recapitalisation in the insurance industry, and 36 per cent of the credit losses of insurers during the financial crash. They also note that although AIG was bailed out for its problems occurred in CDS underwriting, there is little damage on its traditional insurance businesses.

1.1.3 Systemic Risk

The 2007-2009 financial crisis is a systemic crisis with multi-sector disruptions and extensive financial losses, which led to worldwide economic recession. Since the financial meltdown, there is a surge in literature on systemic risk. This section follows Benoit et al. (2016) to review systemic risk from its definitions, its theories and models, and regulations on it.

1.1.3.1 Defining Systemic Risk

There is no widely accepted definition of systemic risk so far. De Bandt and Hartmann (2000) describe systemic risk as the risk with systemic events in the strong sense. Systemic events mainly comprise of shocks and propagation mechanisms, while strong sense in this definition refers to the situation where systemic events finally result in failure of one institution or one market, or failures of many institutions or many markets. International Monetary Fund (IMF), Financial Stability Board (FSB) and Bank for International Settlements (BIS) define systemic risk as "a risk of disruption to financial services that is caused by an impairment of all or parts of the financial system and has the potential to have serious negative consequences for the real economy." The FSB recently developed metrics to identify systemically important institutions, mainly based on six pillars: size, interconnectedness, substitutability, complexity, leverage and liquidity risk, and large mismatches. This research focuses on the negative externalities of systemic risk following the definition suggested by IMF, FSB and BIS.

1.1.3.2 Systemic Risk Models

Following Benoit et al. (2016), this section demonstrates different categories of systemic risk models, which are grouped according to diverse economic mechanisms: systemic risk-taking mechanisms, contagion mechanisms and amplification mechanisms. (see details in Benoit et al. 2016)

(1) Systemic Risk-Taking Mechanisms

Systemic risk-taking mechanisms explain why financial institutions result in similar risk exposures, which leads to the amplification mechanisms, and why they are exposed to large risks, which causes them in default and poses threat to their counterparties via risk propagation.

Correlated investments

If firms invest in correlated assets, they are inevitably to have the same risk exposures. Acharya (2009) proposes two mechanisms between companies: negative externality effect and positive externality effect. The negative externality effect (recessionary spillover) occurs when the failure of an individual bank leads to a decline in the aggregate supply of deposits and therefore a decrease in aggregate investment in the economy. The following rise in the market-clearing rate for deposits will squeeze other banks' profits. The positive externality effect (strategic benefit) results in expansions of the on-going banks due to the transfer of depositors from the failed banks to them, or results in strategic gains for the surviving banks because of the acquisition of the failed banks. Acharya (2009) asserts that negative externality effect is greater than the positive externality effect based on his robust estimations, and he suggest that banks would prefer to invest in more correlated asset portfolios, as banks find it optimal to be more likely to survive or fail together. In the same domain, Farhi and Tirole (2012) note that government interventions are usually associated with a fixed cost, therefore bailouts are optimal only when there are extensive failures in the market, which encourages banks to engage in correlated risk exposures.

Liquidity risk

Benoit et al. (2016) have used the free-rider problem to explain why all banks incline to take illiquid assets. Specifically, when there is a shock to the system, banks with illiquid asset investments could obtain liquidity from other banks in the interbank market. Consequently, no banks would like to be the liquidity providers. They all invest heavily in illiquid assets to pursue higher profits, expecting to rely on others for liquidity support, however this exposes the banking sector to liquidity risk. In addition, maturity mismatch of assets and liabilities – lending in long term by using short-term financing – contributes to liquidity risk in banking as well. The reason why short-term financing is popular among banks is explained in Brunnermeier and Oehmke (2013). They demonstrate the concept of *maturity rat race,* where borrowers tend to issue new debt with shorter maturity as this could dilute the claims of other creditors. Subsequently, all creditors prefer short maturity contracts.

Tail risk

Acharya et al. (2010) propose that large, complex financial institutions (LCFIs) were heavily leveraged by manufacturing tail risks, which were systemic relevant and contributed to the 2007-2009 financial meltdown. They also explain that increasingly intensive competitions, government guarantees without appropriate charges and lax regulations altogether encourage

LCFIs to engage in shadow banking activities such as securitisation. Gennaioli et al. (2013) note that securitisation and diversification in shadow banking system function well in the economy under rational expectations, however these activities will contribute to systemic risks if investors neglect tail risks. Gennaioli et al. (2013) further suggest that policy makers should control the leverage level in banking instead of focusing on capital requirements.

Leverage cycles and bubbles

According to Bernanke and Gertler (1989) and Kiyotaki and Moore (1997), the condition of borrowers' balance sheets play an important role in the dynamics of the economy. Their models suggest that borrowers with higher asset values in economic upturns could borrow more and invest more than in the downturns when asset prices collapse, which amplifies business cycle. Focusing on banks' value-at-risk (VaR), Adrian and Shin (2014) show that firms invest more in expansion periods when VaR is lower, and deleverage in recessions when VaR rises, which results in procyclical leverage. In terms of bubbles, Brunnermeier and Oehmke (2012) have reviewed literature on financial bubbles, and they suggest further research on their origin and how bubbles burst. Allen and Gale (2000) attribute causes of bubbles to agency problems between borrowers and banks. Undertaking risky investments by financing from banks, investors tend to bid up asset prices in that they can shift risks to banks by filing for bankruptcies when face huge losses, which breeds bubbles.

(2) Contagion Mechanisms

Contagion refers to the spread of losses of one financial institution to others through financial interconnectedness. The types of bilateral connections and their potential risks are summarised below.

Balance sheet contagion and networks

Balance sheet contagion refers to risk propagation that is through balance sheet effects. According to Kiyotaki and Moore (2002), indirect balance sheet contagion is trough banks' similar assets holdings that are collaterals for securing bank loans, whilst direct balance sheet contagion is through the direct borrowing and lending connections between firms. Focusing on the interbank market particularly, Allen and Gale (2000b) show that risk-sharing via claims in interbank market is able to prevent default of an individual bank given that there is sufficient liquidity in the market. However, it would result in widespread failures if demand for liquidity from the economy exceeds supply. They further advocate that crisis propagations are different due to various forms of linkages between banks. A complete interbank market network where firms all directly connect to each other perform better, in terms of alleviating financial distress, than incomplete one where some financial institutions are indirectly connected. Eisenberg and

Noe (2001) have developed a model measuring interbank claims that are associated with "cyclical interdependence". In a fully connected networks, Leitner (2005) asserts that banks linking with each other would result in contagion risk, however this would also encourage "private sector bailouts", where banks provide liquidity to troubled banks to prevent contagion. Recently, Gofman (2017) has performed an analysis in the real world by assessing the efficiency and stability of the constructed networks in the U.S. interbank market.

Payment and clearing infrastructures

Interbank payments occur due to the operations of banks' customers. Freixas and Parigi (1998) have investigated the trade-off between gross and net payment systems, facilitating the choice of an appropriate payment system if given a particular scenario. This is based on the analysis that gross payment system would not cause contagion risk but occupies liquidity, whereas net payment system exposes banks to contagion risks but allow banks to keep liquidity[4]. (Adams et al. 2010) Central counterparty (CCP) is associated with potential counterparty risks, and thus many studies have researched on it. Duffie and Zhu (2011) have suggested that in order to mitigate counterparty risk, the number of CCPs should be cut to a single one. According to Heath et al. (2016), CCP provides stability in the market if it is well managed. They claim that according to international standards, a large and systemically important CCP would hold adequate prefunded financial reserves to cover the exposures of the defaults of its largest two participants in "extreme but plausible" market conditions. Even in a range of extreme scenarios where one or multiple participants failed in "beyond plausible" market conditions, or more than two of the participants defaulted, a CCP would distribute the unfunded losses through the system so as to limit the stress transmission. In the same domain, Markose et al. (2017) extends Heath et al. (2016)'s work by considering the European Market Infrastructure Regulation (EMIR) skin-in-the-game requirements for CCPs. They suggest employing digital maps for obligations of G-SIFs at reasonably regular intervals.

Informational contagion

Another form of contagion comes from information externalities. In Chen (1999), depositors that are uninformed of a bank's asset values will run on this bank depending on the information of other banks failures by assuming that returns of banks are correlated. Consequently, a few bankruptcies consequently result in widespread bank runs. Focusing on the connection between price informativeness and liquidity, Cespa and Foucault (2014) propose that liquidity losses in one asset would dry up liquidity of correlated assets, ending up with a widespread liquidity

[4] Galbiati et al. (2010) propose a network formation game for payment systems as a function of liquidity costs.

crisis.

(3) Amplification Mechanisms

Amplification mechanisms explore how individual and small group failures finally turn out to be a systemic one, particularly when it is a simultaneous effect.

Liquidity-driven crises

Amplification could be well explained by the inherent self-strengthening feature of liquidity crises. Shleifer and Vishny (1992) have examined how potential asset buyers determine the liquidation values of assets. In their analysis, when a negative shock hits the industry, all firms in the industry need to liquidate their positions and are not able to buy assets from their peers. This results in asset sales to outsiders at lower prices, which amplifies the downturn. By relating market liquidity to funding liquidity of traders, Brunnermeier and Pedersen (2009) propose two liquidity spirals: a "margin spiral" describes an adverse feedback loop where margin rises when market becomes illiquid; a "loss spiral" refers to losses on one asset leading to asset sales, which further depresses market prices. Both effects would result in asset market collapse and liquidity crisis.

Market freezes

Market freezes are extreme examples of liquidity dry-ups. Disruptions of interbank markets and repo markets in financial crises have generated many studies on them. As early as discussed in Flannery (1996), the lender of last resort is suggested to avoid adverse selection in the interbank market. This is because private creditors cannot obtain and/or estimate the information of banks so that the solvent, but illiquid banks may fail to approach funding. Specifically in repo market where collateral is needed, Gorton and Ordoñez (2014) show that agents will not assess the quality of collateral in normal times as no information emerges or it is costly to get access to the information. Correspondingly, market fragility is building up during market booms. Agents, however, will start to learn about the quality of collateral when a shock occurs. The resulted confidence loss will trigger the freezes of short-term debt markets such as repo market, which increases the likelihood of crises. Focusing on the complexity of the financial networks, Caballero and Simsek (2013) show that since connections and spillovers lead to collective failures in distress periods, banks decline to lend to each other when they know little about their counterparty risk in the complex counterparty system.

Coordination failures and runs

Coordination failures in creditors of financial institutions lead financial firms to be vulnerable by nature, which explains why small shocks could develop to aggregate risk. Diamond and Dybvig (1983) have shown that bank deposit contracts are more efficient than exchange markets in terms of providing liquidity and risk sharing. However, this advantage also leaves banks subject to runs. There are multiple equilibria with various confidence levels in banking: when the confidence levels of depositors in banks are relatively high, the equilibrium is that maturity transformation in banking works well; when confidence levels are low, depositors will be panic and run on banks. Martin et al. (2014) have explored whether and to what extent will the fragility in short-term lending market especially in repo market give rise to financial institution runs. They find that the possibility of repo runs due to market-wide changes in expectations relies on market microstructures.

1.1.3.3 Regulations

There are updating regulatory rules and tools targeting on the aforementioned systemic risk models, which will be reviewed in this section. (see details in the survey of Benoit et al. 2016)

Basel III requires banks to hold at least 8.5% Tier 1 capital ratio – Tier 1 capital/risk-weighted assets – to target *solvency risk*. 2.5% of risk-weighted assets are the lower thresholds as the "conservation buffer", below which dividend distributions of banks are forbidden. Basel Committee on Banking Supervision (2014b) has also imposed a non-risk-based 3% limit of leverage ratio – Tier 1 capital/total assets – on banks. The pillar of leverage was removed from Basel II but reintroduced in Basel III in response to the 2007-2009 financial crash. The main differences between Tier 1 capital ratio and leverage ratio is that the former considers risk-weighted assets (RWA), while the latter focuses on total assets. RWA is introduced to base capital requirements on risk categories of bank assets, which prevent banks from huge capital losses when a particular type of asset is considerably written down.

Sectoral capital requirements and caps on loan-to-value ratios are the macro-prudential tools on *correlated investments.* Specifically, sectoral capital requirements deter banks to lend into particular sectors by imposing higher capital ratios, while caps on loan-to-value ratios focus on mortgage loans.

For *liquidity risk,* Basel Committee on Banking Supervision (2013) has proposed liquidity coverage ratio that impose banks to maintain enough High Quality Liquid Assets (HQLA) to cover their short term liabilities (within 30 days). HQLA are assets that are easily and quickly to be liquidated. There are three categories of HQLA: Level 1, Level 2A and Level 2B. Level 1 refers to highly liquid assets with no haircut. Level 2A include GSE (government sponsored enterprise)-guaranteed assets that receive 15 per cent haircut. Level 2B assets are subject to 50 per cent hair cut and include common equity and corporate debt securities. Basel Committee on Banking Supervision (2014a) on the other hand, directly eases the general liquidity risk by restricting the upper level of short-term debt.

Stress tests are performed to deal with *tail risks.* Targeting on *leverage cycles,* Basel III has proposed countercyclical capital buffers, which would alleviate the procyclicality caused by the Basel capital requirements that are loose in prosperity and tight in distress. Academics have recommended some reforms on risk-taking as well. Acharya et al. (2013) suggest that regulators should impose a "tax" on financial institutions according to their expected losses conditional on a systemic crisis. Questioning the private money creation, which causes negative externality where excess short-term debt issued from banks, Stein (2012) suggests open-market operations to monitor those externality. In Bianchi and Mendoza (2013), a "macro-prudential debt tax" as an optimal policy is suggested to impose on financial institutions if there is a high expected probability of crisis.

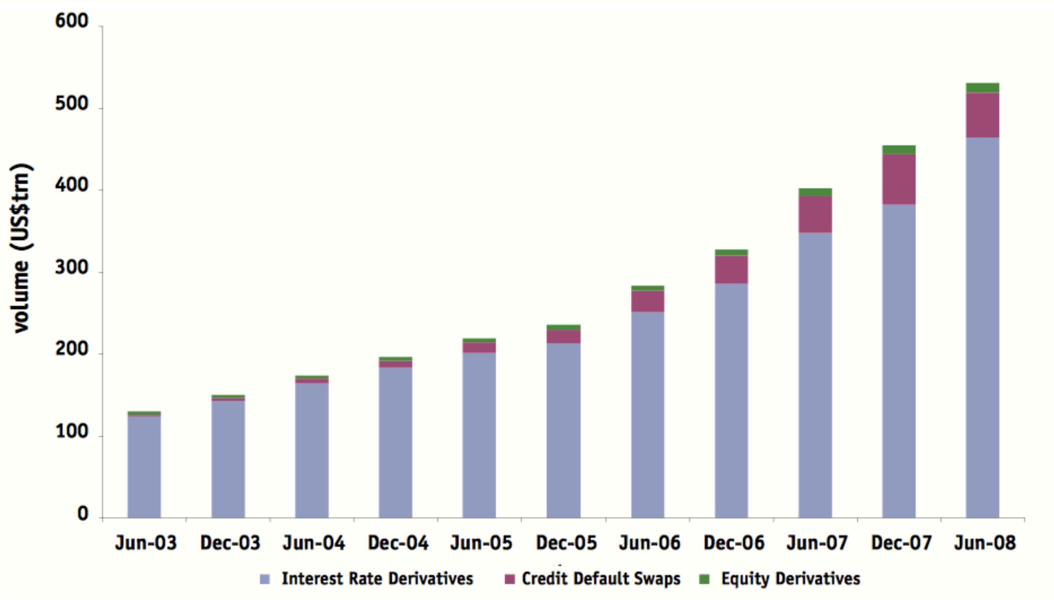
Basel Committee on Banking Supervision (2014a) finally acknowledges and inserts *contagion* as risk to control, however it is still vague on how to measure contagion. Academics have proposed alternative regulatory reforms to tackle contagion. Some of them suggest that capital requirements should be depending on the systemic relevance of a company rather than the firm-level risk of the company. (Allen & Gale 2007; Alter et al. 2015) Instead of supervising bilateral linkages, Rochet (2010) propose to transfer interbank trades to central counterparty (CCP) system and enforce regulations on CCP. Financial Stability Board (2015) suggests that over-the-counter (OTC) derivatives should be traded in exchanges and through CCPs.

Deposit insurance has also been improved to prevent runs on financial institutions. For example, the value of it has been increased in the euro area since the Cyprus bailout in 2013. Due to the fragility of interbank markets, European Central Bank (ECB) has considerably replaced the role of the interbank market as the lender of the last resort for banks during the financial crisis. In U.S., Troubled Asset Relief Program (TARP) is implemented to inject capital into the market in 2008 to prevent substantial bank failures. However, some academics point out the disadvantage of government rescue as in Allen et al. (2017), which claim that government guarantees distort the market and result in bank failures. To respond to the 2007-2009 financial crisis and the questions from the public regarding government reliefs, Dodd-Frank Act was passed in 2010, aiming to stop bailouts and protect the taxpayers. Other popular recent regulations would be to publicly release stress test results such as the Supervisory Capital Assessment Program (SCAP) led by the Federal Reserve (Fed) and the disclosures of bank risks from the European Banking Authority (EBA).

1.1.4 CDS Market in the 2007-2009 Financial Crisis

Credit default swap (CDS) transactions were prevalent prior to the subprime mortgage crisis among the NBFIs and were believed to be responsible for the occurrence of systemic risk. AIG, MBIA and AMBAC that were in distress during the financial meltdown were all associated with CDS.

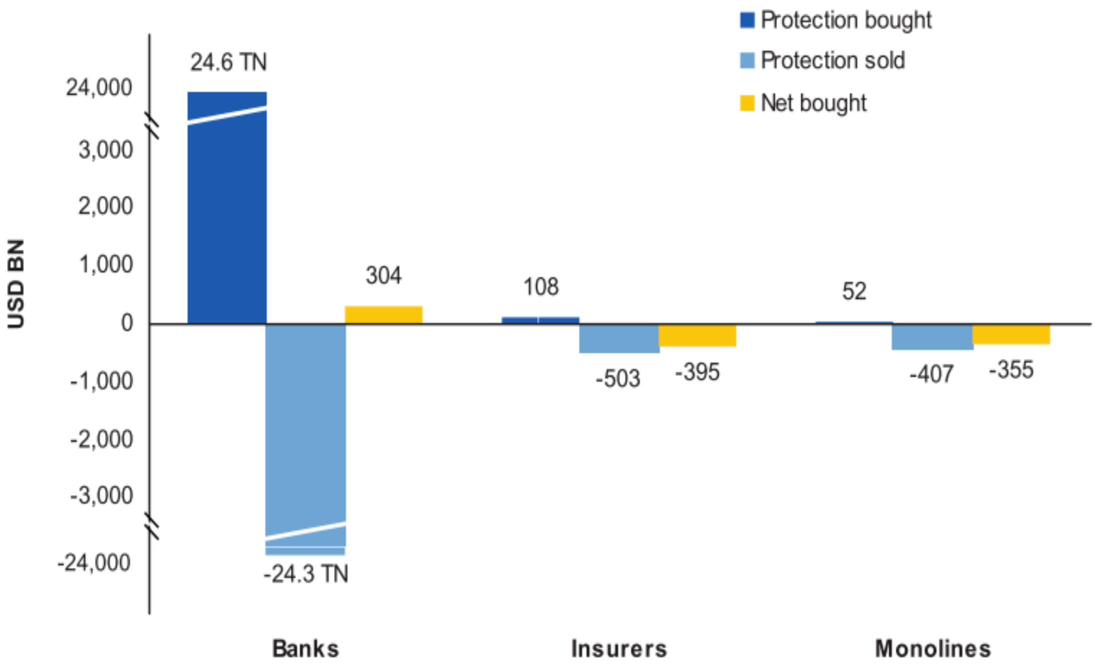
A single-name credit default swap acts as an insurance product specified over a period, with its payoff triggered on the condition of credit events of the underlying instrument–a reference asset or a reference entity. Specifically, a protection buyer purchases CDS from a protection seller by paying a periodic premium, also called CDS spread. This contract allows the protection buyer to transfer the default risk of the reference entity to the protection seller. With all else being equal, the higher the CDS spread, the higher the credit risk of the underlying assets. When default of an asset or bankruptcy of an underlying entity occurs, the protection seller will have to pay compensation to the protection buyer. Schich (2009) summarises two types of CDS: covered CDS refers to the situation where the protection buyer is holding the reference assets being insured by CDS. As for naked CDS, the credit protection buyer does not own the reference obligation. Therefore, covered CDS is more like an insurance contract relative to naked CDS, which is mainly driven by speculation motives.



Source: Turner (2009)

Figure 4 OTC Derivative Trading Volume by Type

As shown in **Error! Reference source not found.**, Turner (2009) reports that the over the counter (OTC) derivative trading volume had experienced a rapid growth in the past decades particularly from 2006 to 2008, with its gross nominal value as $60 trillion in 2007 since its generation in the mid 1990s. Markose et al. (2012) note that CDS became popular when "Credit Risk Transfer" (CRT) scheme of Basel II, the Joint Agencies Rule 66 Federal Regulations 56914 and 59622 allowed banks to use CDS or financial guarantees to transfer credit risks of their underlying exposures[5] to an AAA protection provider[6]. ECB (2009) has compared the CDS buyers and CDS sellers by sector as shown in **Error! Reference source not found.**, which shows that insurers and monolines were the major issuers and banks were the net buyers in December 2006. In this way, the credit risk pressure on banks was alleviated and their capital requirements were reduced accordingly, however risks were transferred to NBFIs, especially insurers given their active operations in CDS trading.



Source: ECB (2009)

Figure 5 CDS Bought and Sold by Sector in December 2006

Markose et al. (2012) assert that CDS premiums have inherited weakness of self-reflexive characteristics that has been shown to contribute to systemic risk. CDS spreads not only reflect the credit risk status of the reference entity, but also in turn accelerate default event in that the rise of CDS spreads will result in credit rating downgrades, cost of capital increases and stock market devaluations (Markose et al. 2012). In

, Markose et al. (2012) show that CDS contracts are also sold to a third party (D), who

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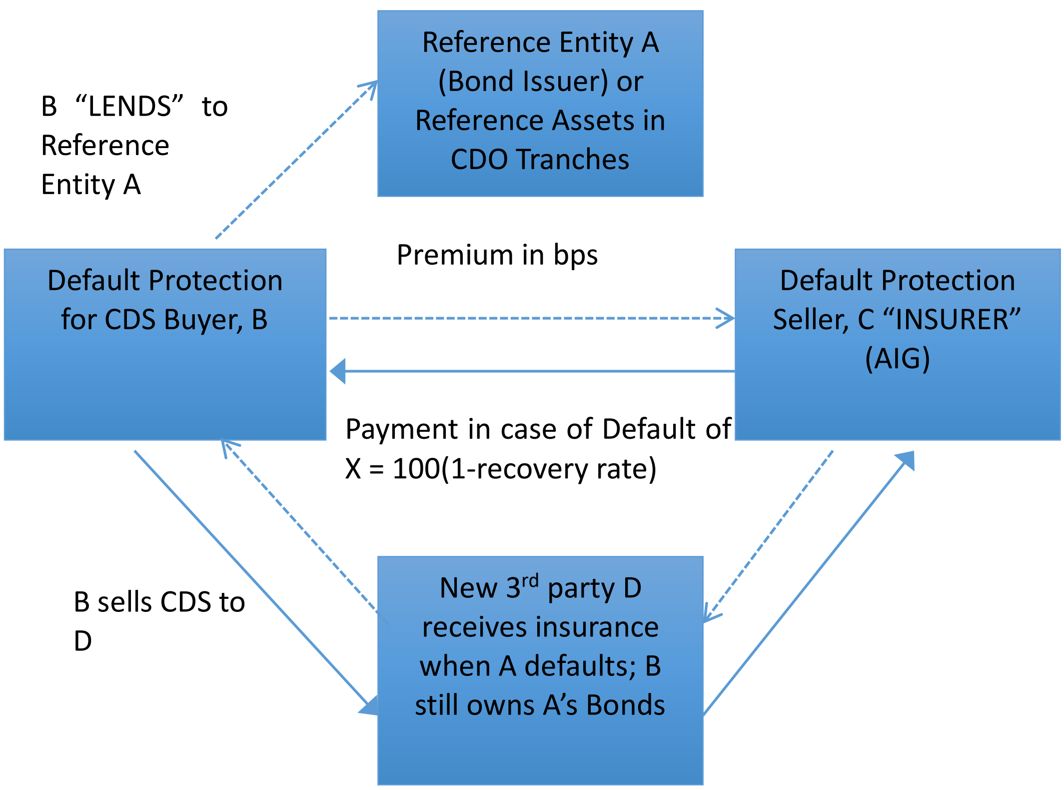
[5] Such as MBS on the balance sheets of banks

[6] Such as AIG, hedge funds and monolines

does not hold the underlying assets of the reference entity. This is the so-called naked CDS. In this case, D is motivated to short the reference entity to trigger the default event and thus obtains the payment from the CDS contract (Bear Raid). Even if an investor, such as the protection buyer B, owns the reference assets and buys CDS for protection, i.e. the covered CDS, he or she will prefer a default event to occur in order to benefit from the payments on CDS. This is the so-called empty creditor phenomenon. (see Bolton and Oehmke, 2011) The strategy of "offsets" used by CDS participants to manage liquidity requirements will lead to potential systemic risk when the chains of CDS obligations increase and merge. Specifically, in Figure 6, B lends to the reference entity A and buys CDS contracts from protection seller C to protect the underlying assets that B holds. When CDS spreads increase, B may adopt the offsets strategy by selling CDS to a third party D to benefit from the difference between the premium paid to C and received from D. This is an open chain that leaves B's obligations net to zero, while D will obtain the final payments of the CDS contracts if default is triggered. In the case of a closed chain, i.e., C sells to B, B sells to D and D sells to C, the aggregate net CDS payments for all parties are zero if all of B, C and D are solvent when a default event occurs. However, if one of the parties faces liquidity risk or goes bankrupt, then every player in this closed chain will fail to fulfil their obligations to each other, which results in systemic event.



Source: Markose et al. (2012)

Figure 6 Credit Default Swap Structure
The figure illustrates the structure of credit default swap. Solid arrow denotes the direction of CDS sale. Recovery rate is the ratio of the reference asset value at default to its face value.

As mentioned earlier, CDS sellers protect CDS buyers against the credit risk of underlying assets or underlying entities through CDS contracts, thus counterparty risk is inevitable during the transactions. Duffie et al. (2010) conclude that counterparty risk could develop to systemic risk as follows: (1) the failure of one financial institution with enormous derivatives portfolio could lead to huge losses in this firm's derivatives transactions, which poses threat to its counterparties; (2) in order to avoid the potential losses, counterparties would reduce their exposures to the problematic financial institution, which in turn exacerbates the failure of the troubled financial institution; (3) a "fire sale" with one market participant failing initially could contribute to huge price fluctuations when counterparties attempt to change their positions with this problematic financial institution, or when every market player tries to exchange risky assets to safe ones. In this scenario, the fire sale leads to massive losses for most market participants, even if they are not direct counterparties to the distressed financial institution.

Considering the aftermath of the disruption in the CDS market, the failures of CDS issuers during the financial crisis of 2007-2009, and the relationship between counterparty risk and systemic risk, this thesis exploits the role of CDS information in capturing risks.

1.2 Motivations and Contributions

1.2.1 Motivations

Existing studies of the systemic relevance in the insurance sector have produced some mixed findings. Most of the papers conclude that insures are relevant to systemic risk to some extent, but they are less important than banks (Baluch et al., 2011; Billio et al., 2011; Girardi and Ergün, 2013; Chen et al., 2014), or they are affected by others rather than acting as the risk contributors (Berdin and Sottocornola, 2015). Previous research also suggests that it is the non-core business instead of the traditional insurance activities of the insurers that contribute to systemic risk (Cummins and Weiss, 2014; The Geneva Association, 2010), or only some types of insurers are systemic relevant (The Geneva Association, 2010; Chen et al. 2013). By applying analyses into multiple markets, Bernal, Gnabo and Guilmin (2014) conclude that insurers contribute the most to systemic risk in U.S., and are the least risky sector in the Eurozone. The contradicting conclusions between Bernal et al. (2014) and other studies regarding sector risk rankings in the U.S. market motivated this research to further investigate the risk contributions of the insurance sector through a multi-method systemic risk analysis. Last but not least, Baluch et al. (2011) recommend that one should not concentrate on which industry is more important as systemic risk contributors, but on the strength of the connections between the sectors. In order to shed a light on this issue, this thesis quantifies the linkages beween pairwise sectors in an innovative way, which is through the sector connectedness analysis in Section 5.

Academics have also compared systemic risk estimations using both CDS and other data. It is accepted that CDS is better than equity returns or bond spread in terms of capturing default (Huang et al., 2011); CDS spreads reflect counterparty risk and measure the joint default risk of pairwise banks (Giglio, 2014); CDS data mirrors the underlying value of financial institution's debt that might be under government guarantees (Acharya et al., 2017). However, there is currently no research using manifold leading systemic risk methodologies together with firm-level risk measures to investigate the role of the data type in risk evaluations.

A few previous papers have reviewed and compared various competing systemic metrics. Bisias et al. (2012) and Benoit et al. (2016) have investigated multiple systemic risk measures by concentrating on distinct perspectives. Both of them suggest the soundest risk measure should encompass multi-directional information and have practical functions to facilitate regulators or other users. However, these two studies haven't recommended any one or a few risk metrics to be superior. Rodríguez-Moreno and Peña (2013), and Arsov et al. (2013) have tested and identified the most effective systemic risk analytics. Nevertheless, they suggest different best-performed risk indicators and both have not considered a new advanced systemic risk metric – SRISK, which is included in my thesis.

1.2.2 Contributions

Different from previous studies, this thesis includes firm-level risk analysis in addition to systemic risk estimations to explore sector risk ranking among banks, insurers, and non-financial institutions (NFIs). Firm-level risk and systemic risk together are to produce multi-facets risk profiles of companies.

This thesis is the first one that has performed all of the most frequently cited[7] market-based systemic risk measures and the most widely accepted firm-level risk measures aiming to achieve more convincing outcomes.

This study has improved the existing research on comparing the role of CDS data and non-CDS data in risk estimations by expanding the comparison samples: In addition to systemic risk measures that are originally constructed on CDS data, the research has also applied CDS data to methodologies that are initially designed for equity returns ($\Delta CoVaR$, Granger causality tests, and impulse response function (IRF)) to enhance comparability.

[7] The most cited papers regarding the systemic risk measures are presented in Figure 1 of Benoit et al. (2016)

This study proposes IRF as a risk indicator to measure systemic risk.

Previous research rarely performs statistical significance tests on systemic risk methodologies. This study fills the gap by applying Wilcoxon signed-rank test (significance test) and Conover-Iman test (dominance test) on all risk measures in the thesis.

This thesis distinguishes the two dimensions of systemic risk – systemic importance and systemic vulnerability – of a company through a pairwise analysis. This risk classification is usually neglected by previous literature.

1.3 Research Questions

The thesis tries to shed a light on: (1) whether insurers are riskier than banks and NFIs in terms of both firm-level risk and systemic risk; (2) whether CDS data is better than non-CDS data in capturing the subprime mortgage crisis through a multi-method risk analysis; (3) how firm-level risk measures correlate to systemic risk measures; (4) whether the risk methodologies applied in this thesis have the predictive power of the 2007-2009 financial distress and which risk metric is superior to others.

1.4 Methodologies and Data

This research applies institutions' firm-level risk assessments as well as systemic risk evaluations to obtain relatively comprehensive risk analysis of the banks, insurers and NFIs in the sample. Firm-level risk measures include volatility, VaR, expected shortfall, beta, CDS spread, and Z-Score (Mare et al. 2016). These firm-level risk measures are meant to capture the instability of a firm from different aspects and are using diverse data sources. However, firm-level risk approaches only capture the riskiness of the institution itself that is affected from the exogenous shocks. They have no considerations of the connections between companies, or the negative externalities of one or a few failures on other institutions in the system, i.e., the endogenous risk. Therefore, micro-prudential regulations based on firm-level risk metrics failed in the 2007-2009 financial meltdown. Since then, regulators realised the necessity for appropriate macro-prudential policies established on systemic risk indicators, which attempt to regulate market participants at a macro level. Academics have also proposed multiple systemic risk methodologies to detect systemically important financial institutions on which the macro-prudential regulations can impose more strict policies. Systemic risk measures adopted in this study are $\Delta CoVaR$ (Adrian and Brunnermeier 2016), $\Delta CoRisk$ (CDS-based $\Delta CoVaR$), equity-based Granger-causality tests (Billio et al. 2012), CDS-based Granger-causality tests, equity-based impulse response functions (IRF), CDS-based IRF, Distress Dependence Matrix (DiDe) (Segoviano and Goodhart, 2009) and SRISK (Brownlees and Engle, 2016).

In this thesis, both firm-level and systemic methodologies are applied into the same dataset, 96 listed international companies that comprise 32 banks, 32 insurers and 32 NFIs to evaluate the risk contributions of the insurance sector. Moreover, both CDS data and non-CDS data are applied into the risk analyses to explore whether CDS-based risk methods perform better than non-CDS-based risk methods. In firm-level risk assessments, volatility, VaR, expected shortfall and beta employ equity data, CDS spread is the premium of the 5-year CDS contract, and Z-Score is based on balance sheet data. With regard to systemic risk metrics, CDS spreads are the inputs in $\Delta CoRisk$, CDS-based Granger causality, CDS-based IRF, and DiDe. Non-CDS data are required in $\Delta CoVaR$, equity-based Granger causality, equity-based IRF, and SRISK.

1.5 Empirical Findings

Empirical Results from sector connectedness analysis reveal that banks and insurers are strongly connected with each other, but both of them have relatively weak connections with NFIs (consistent with Billio et al. (2011)). Furthermore, systemic risk analysis in this thesis disclose that banks are the main risk triggers that contribute risk to other companies, while insurance companies are the key risk receivers that are affected most by other companies. This is in line with Baluch et al. (2011), Billio et al. (2011); Girardi and Ergün (2013), Chen et al. (2014), and Berdin and Sottocornola (2015). There are also some findings different from exiting research: firm-level risk results (systemic risk results) suggest that insurers have higher credit risk than other sectors (insurers contribute more credit risk to others), while banks have higher overall risk as indicated by equity-based risk measures (banks contribute more equity-based risk to the system).

CDS-based and non-CDS based risk indicators produce dissimilar risk rankings among banks and insurers, which suggests that multiple data types should be included altogether in risk analysis to produce a multi-facet risk profile of a company. What’s more, structural break tests on both firm-level risk assessments and systemic risk assessments reveal that the CDS-based risk measures switches to higher values at earlier stage than the non-CDS-based risk indicators. This denotes that credit risk is able to signal early warnings of crisis.

Rank correlations between firm-level risk indicators and systemic risk indicators show that firm-level risk measures are weakly correlated with systemic risk measures, indicating that firm-level risk is not able reflect some information that are only contained in systemic risk. In addition, firm-level risk has shown higher correlation with a company’s systemic vulnerability than with the company’s systemic importance. This implies that the firm-level risk of a company roughly represents the risk magnitude of this company as a risk receiver rather than a risk contributor.

The empirical results from cross-sectional regressions demonstrate that DiDeSV, LRMES and SRISK are superior to firm-level risk measures and other systemic risk measures in terms of their ability to predict crisis.

1.6 Outline of the Thesis

The remainder of the thesis is organised as follows.

Section 2 reviews studies that are investigating on the research questions in this thesis. Firstly, it reviews literature on existing CDS-based and non-CDS-based systemic risk measures. It then reviews the systemic relevance in insurance, following which is the literature review on the comparison between firm-level risk and systemic risk. The comparison and empirical validation of systemic risk metrics are presented as well.

Section 3 demonstrates the empirical firm-level risk assessment. The firm-level risk measures are applied to 96 global companies from 2005 Q1 to 2014 Q4 to provide company risk as well as sector risk rankings. Statistical significance tests have been applied to all risk estimations. The results differences in the risk estimations using diverse data inputs are compared, and the structural break tests are performed to examine the time points when risk metrics transfer from a stable mode to a volatile mode.

Section 4 performs the empirical systemic risk assessment. This section is based on the same dataset as Section 4, with sample period from 2005 Q1 to 2014 Q4 (2005 to 2014 for Granger-causality tests and IRF), and it includes three analyses: industry connectedness analysis is to quantify the connection intensity between sectors; systemic importance and systemic vulnerability analysis are to capture the two dimensions of systemic risk; sector risk ranking compares the systemic relevance of insurance companies with that of banks and NFIs. Statistical significance tests have been applied to all systemic risk evaluations. The performance of the CDS data in systemic risk evaluations is explored in contrast to that of the non-CDS data. Structural break tests are carried out as well in this section to investigate which risk methodology based on what type of data is able to provide earlier risk warnings.

Section 5 presents the rank correlation between firm-level risk methods and systemic risk methods. This section also tests the ability of all the risk measures to predict the subprime mortgage crisis, i.e. regress the realised equity returns (CDS returns) during the period from 2007 Q3 to 2008 Q4, on the values of the risk methodologies during the period of 2006 Q1 to 2007Q2.

Chapter 6 summaries the solutions to the research questions and points out the limitation of the thesis and the possible improvements in the future work.

2 Literature Review

This section reviews literature on CDS-based and non-CDS-based systemic risk assessments in Section 2.1, systemic relevance in the insurance sector in Section 2.2, the comparison between firm-level risk and systemic risk in Section 2.3, and empirical validation and comparison of systemic risk methodologies in Section 2.4.

2.1 Reviews on Systemic Risk Assessment

Following Benoit et al. (2016), systemic risk theories reviewed in Chapter 1 are categorised by the source of systemic risk. The risk source types include systemic risk-taking, contagion, and ampliction. Since systemic risk methodologies focusing on one source may require specific unpublic information, these methodologies are not easilied to be widely applied. Market-based risk measures, however, overcome this issue by using public data that reflects general risk condition of a company that is decided by the market, instead of relying on unaccessible private information to capture a particular source of risk (Benoit et al. 2016). Given this, this thesis focuses on market-based systemic risk measures. Particularly, CDS-based and Non-CDS-based systemic risk measures are reviewed in this section as this thesis aims to compare the results of CDS-based and non-CDS based risk estimations.

2.1.1 CDS-Based Systemic Risk Assessment

By comparing CDS data and equity data, Jorion and Zhang (2007) have assessed how intra-industry information is transferred among companies following credit events[8]. They have propose two types of default correlations: "contagion effect"[9] and "competitive effect"[10]. Jorion and Zhang (2007) have employed a standard event study method to assess the market reactions of industry rivals around credit events, and they find that contagion effects are better captured in the CDS market than in the stock market.

In contrast to Jorion and Zhang (2007), Segoviano and Goodhart (2009) adopt copula approach instead of correlation method to measure the non-linear dependencies across banks. Segoviano and Goodhart (2009) have proposed Distress Dependence Matrix (DiDe) to estimate the consitional probability of default (PoD) of a company. Segoviano and Goodhart (2009) have compared three ways to estimate PoD: (1) the structural approach (SA); (2) derive from CDS spreads; (3) compute from out-of-the-money (OOM) option prices. They note that SA has its problem of parameter choices and it doesn't produce consistent results. OOM also has the

[8] Chapter 11 bankruptcies, Chapter 7 bankruptcies and jump event

[9] Exists when distress across companies is due to common economic factors, counterparty risk, and updating of beliefs.

[10] Occurs when customers reduce or avoid trading with the troubled firm and turn to its competitors.

problem of inconsistent estimates and it lacks data for implementation. Although CDS spreads present disadvantages such as overstatement of a bank's "fundamental" risk when the particular CDS market is illiquid or when there is generalized risk aversion in the market, these are usually short-term issues and usually signal a correct direction of distress in the long run. Consequently, Segoviano and Goodhart (2009) decide to use CDS spread to obtain POD. The banking stability measures proposed by Segoviano and Goodhart (2009) has advantages as follows: (i) can be implemented from a limited dataset; (ii) embed both linear and non-linear distress dependencies among banks; and (iii) allow the changes of inter-dependence structures at specific time points. However, since CDS data is employed in their methodology, results using the Segoviano and Goodhart (2009) may also be inaccurate when CDS stata is illiquid.

Similar to Segoviano and Goodhart (2009), Oh and Patton (2016) also uses copula models measuring dynamic high-dimensional distributions following the ideas of high-dimensional dynamic conditional correlation (Engle 2002) and time-varying distributions (Creal et al. 2013). Different from Segoviano and Goodhart (2009), however, Oh and Patton (2016) have combined copula models that reflect conditional dependence structure, with models of univariate distributions. By appling time-varying copula models to CDS spreads of 100 U.S. firms from 2006 to 2012, Oh and Patton (2016) find that although probability of default for individual firm substantially declined after peaked in the 2007-2009 financial meltdown, the joint probability of default, which represents systemic risk, has remained high and is much higher now than the pre-crisis period.

Similar to the idea of marginal expected shortfall (MES) (Acharya et al., 2011), which will be discussed in the next section, Distress Insurance Premium (DIP) is proposed by Huang et al. (2011) that exploit CDS data instead of equity data. Huang et al. (2011) define their risk measure as the insurance premium to protect against the distressed losses in a banking system. Huang et al. (2011) suggest that systemic risk in banking system is driven by the default risk premium at the beginning and by the liquidity risk premium later. They also find that a bank's contribution to systemic risk is approximately linear with its default probability, but nonlinear with its size and asset correlations with other institutions.

Instead of using only bond or CDS data separately, Giglio (2014) measures systemic risk by combining bond prices and CDS spread. He contends that CDS spreads reflect counterparty risk and measure the joint default risk of pairwise banks, while bond prices mirror the individual default probabilities. Using linear programming, Giglio (2014) constructs tightest upper and lower bounds on the joint probability of default of multiple banks given the individual and pairwise default probabilities to capture systemic risk. Giglio's methodology is an improvement in measuring the joint probability of systemic distress in that there are no assumptions on return distributions, whereas Segoviano and Goodhart (2009) and Huang et al. (2011) assume multivariate normality of returns in their papers. Unlike the indications from other systemic risk measures, Giglio (2014) finds that his methodology does not signal higher default probabilities during the early stage of the 2007-2009 financial crisis, and he claims that the combination of CDS data and bond data capture the timing of the build-up of systemic risk. However, there are also disadvantages in Giglio's approach: unobserved liquidity process in bond market may lead to inaccurate estimations of individual default probabilities; mean values of the CDS data across counterparties of each bank are used instead of counterparty-specific values; bounds are computed using risk-neutral probabilities of distress instead of objective probabilities.

Rodríguez-Moreno and Peña (2013) have also compared market-based systemic risk measures by using various data sources–interbank rates, stock prices and CDS spread. Different from other literature, Rodríguez-Moreno and Peña (2013) have compared a series of risk measures using the following methods: (1) correlation of the risk methodologies with an index of systemic risk events and policy actions, (2) Granger-causality tests, and (3) Gonzalo and Granger (GG) metric. They agree with aforementioned research that that CDS-based measures perform better than the approaches employing interbank rates or stock prices, implying that CDS market provides more accurate signals of potential financial crisis than other markets.

Considering the features of CDS data, Acharya et al. (2017) employ CDS data in marginal expected shortfall (MES)[11] in addition to equity returns. They suggest that CDS data might be superior to equity data to evaluate market value losses of the firm's assets. They find that MES based on equity and CDS are both able to predict the distressed financial institutions in the financial crisis.

In sum, it is widely believed that CDS is better than any other types of information to capture default and counterparty risk (Huang et al. (2011), Rodríguez-Moreno and Peña (2013), Giglio (2014)), and that contagion effects are better captured in the CDS market than in the stock market (Jorion and Zhang (2007)). Following this thesis includes CDS data in addition to equity data in systemic risk evaluations

2.1.2 Non-CDS-Based Systemic Risk Assessment

The most influential non-CDS-based measures are marginal expected shortfall (MES) and systemic expected shortfall (SES) from Acharya et al. (2017), SRISK from Acharya et al. (2012)

[11] Details will be discussed in next section

and Brownlees and Engle (2016), and $\Delta CoVaR$ from Adrian and Brunnermeier (2016). Some other frequently cited measures will be summarised as well.

Acharya et al. (2017) propose marginal expected shortfall (MES) that quantifies the equity loss of a firm in the tail of the market's loss distribution. Systemic expected shortfall (SES), by taking into account both a company's MES and leverage, measures the institution's capital loss when the financial system is undercapitalized. Acharya et al. (2017) conclude that MES has the ability to predict the crisis, however, firm-level risk such as expected shortfall, volatility and beta have less explanatory power. Finally, they suggest that a system tax, stress tests or recapitalisation of the troubled financial institutions will be effective tools for macro-prudential regulation. Comparing with DIP (Huang et al. (2011)), which also captures each bank's expected loss conditional on the system being in distress, MES defines the extreme condition as the tail of the percentile distribution rather than a given threshold of portfolio loss in DIP. Furthermore, in MES, the probabilities in the tail event are normalized to sum to 1, while they are not normalized in DIP. Finally, the most crucial difference is that DIP uses CDS data, whereas MES is based on equity return data.

Acharya et al. (2012) and Brownlees and Engle (2016) have extended MES to SRISK by considering leverage and size of financial firms. SRISK estimates the expected capital shortfall of a financial institution conditional on a substantial market decline. Brownlees and Engle (2016) have applied SRISK to the top US financial institutions in the subprime mortgage crisis, and it is able to identify troubled firms as early as 2005 Q1. Aggregate SRISK, the sum of the positive values in SRISK and the representative of the total capital losses in the whole system, could recognise all the crises stages. Brownlees and Engle (2016) have verified that SRISK has the ability to predict the capital injections of the Troubled Asset Relief Program (TARP). The advantage of SRISK is that it merges market and balance sheet information. Moreover, compared with SES, SRISK has no structural assumptions and does not require a realisation of the systemic crisis for evaluation.

SES and SRISK are both grounded on MES, however, MES only measures risks of firms affected by the market turbulence, without considering the role of financial institutions as risk triggers. $\Delta CoVaR,$ another leading systemic risk metric proposed by Adrian and Brunnermeier (2016), takes this into account. It estimates the difference in the value at risk (VaR) of the entire system conditional on a company being in extreme event relative to its median state. They find that $\Delta CoVaR$ could be significantly explained by institutions' systemic relevant characteristics such as leverage, maturity mismatch, sizes and asset values. In addition, a forward-$\Delta CoVaR$

has the ability to predict the realised $\Delta CoVaR$ in the 2007-2009 financial meltdown. However, $\Delta CoVaR$ has its drawbacks as well. Acharya et al. (2012) and Acharya et al. (2017) point it out that since $\Delta CoVaR$ is the system's VaR conditional on the default of each company, the conditions are not constant cross-sectionally. $\Delta CoVaR$ therefore, might demonstrates that the systemic risk levels of two firms are equal if these two institutions have the same return correlation with the market even if they actually have distinct return volatilities.

In addition to these most popular methodologies, another most cited study is from Billio et al. (2012) who employ principal-components analysis and Granger-causality tests to assess the inter-linkages between equity returns of banks, broker-dealers, insurers and hedge funds. Although Billio et al. (2012) is using market data for Granger-causality tests, which should capture general systemic risk of a company, their work focuses on the contagion (the second economic mechanisms for systemic risk models in Chapter 1) by performing company connecteness analysis. They show that their econometric network measures could recognise the crisis periods and have the out-of-sample forecasting power. Their findings regarding the risk connectedness among the four sectors will be discussed in Section 2.2.

An alternative acknowledged systemic risk approach comes from Diebold and Yilmaz (2009), who also base their methodology on vector autoregressive (VAR) models to estimate the connections between asset returns/asset volatilities of companies. They focus on variance decompositions, which divide the forecast error variances of each variable into a few parts that are attributed to different shock sources. They propose a *Spillover Index* as the ratio of the *cross variance shares* (spillovers) to the total forecast error variance. By using equity index returns in the spillover analysis from the early 1992 to 2007, Diebold and Yilmaz (2009) conclude that return spillovers have shown an rising trend with no spikes, while volatility spillovers have experienced no trend but spikes.

2.1.3 Summary

Quite a few market-based systemic risk measures have been proposed so far as discussed above, however, this thesis has employed $\Delta CoVaR$ (Adrian and Brunnermeier 2016), Granger-causality tests (Billio et al. 2012), Distress Dependence Matrix(DiDe) (Segoviano and Goodhart 2009) and SRISK (Acharya et al. 2012, Brownlees and Engle 2012). The reasons of the selection are listed as below.

First, this thesis only focuses on the most accepted and highly cited[12] market-based systemic risk measures. Apart from the risk methodologies this thesis adopts, Systemic

[12] The highly cited market-based systemic risk measures are summarised in the Figure 1 of Benoit et al. (2016)

expected shortfall (SES) (Acharya et al. 2017) and Distress Insurance Premium (DIP) (Huang et al. 2011) are also popular market-based systemic risk measures. This thesis does not include SES because SRISK is similar to and relatively more advanced than SES. DIP is not chosen because it has a similar idea to MES, which is the basis of SRISK, therefore this thesis only focuses on SRISK.

Second, network analysis for CoVaR/CoRisk/Granger causality are available but not adopted in this thesis in that this study focuses on statistical risk measures, therefore structural risk methodologies (network analysis) is exclused.

In addition to existing systemic risk measures in the previous studies, this thesis extends Granger-causality tests and proposes impulse response function (IRF) to evaluate systemic risk by capturing impulses and responses of pairwise companies.

This thesis would like to compare results of systemic risk measures using CDS and non-CDS data, therefore CDS data is also substituted into equity-based systemic risk measures. Following this, risk indicators in this thesis include: $\Delta CoRisk$ (CDS-based $\Delta CoVaR$), $\Delta CoVaR$, CDS-based Granger-causality tests, Equity-based Granger-causality tests, CDS-based IRF, Equity-based IRF, DiDe, LRMES (long run maginal expected shortfall)[13] and SRISK.

2.2 Reviews on Systemic Relevance in Insurance

While most research on systemic risk is associated with the banking sector, there has been a growing number of studies focusing on the systemic relevance of insurance companies, a subsector of NBFIs, during the 2007-2009 financial crisis.

The Geneva Association (2010) has categorised insurance companies into four types[14]: insurers with limited banking activities, bank-insurance conglomerates, insurers with wholesale banking operations, and monoliners/financial guarantee. They conclude that only the latter two types were the systemic risk triggers. The Geneva Association (2010) suggests that it is not the insurer itself but its activities that matter. Specifically, they have analysed the main operations of insurers based on FSB's systemic relevance criteria [15] –size, interconnectedness, substitutability, complexity, leverage, liquidity risk, and large mismatches– as well as the criterion of time suggested by International Association of Insurance Supervisors (IAIS). Insurers' activities that are investigated include investment management, liability origination, risk transfer and capital management. The Geneva Association (2010) finds that

[13] LRMES is the basis of SRISK, and this thesis carries out analysis on it as well.
[14] See Section 1.1.2
[15] Criteria for identifying systemically relevant institutions

only two non-core activities of insurance companies are potentially relevant to systemic risk: derivatives trading such as CDS trading on non-core balance sheets; poor management of short-term funding raised from commercial paper or securities lending. Based on these analyses, they further suggest regulatory measures to mitigate potential systemic risk to supplement Solvency II.

Baluch et al. (2011) have summarised historic insurance crises, and have analysed the role of insurance companies in the subprime mortgage crisis. They claim that although insurers are less associated with systemic risk than banks, their systemic relevance has grown in recent years due to their increasing connections with banks and rising non-core activities. Accoding to them, insurers have increasingly moved to capital markets and alternative risk transfer mechanisms to mitigate risks on their balance sheets, which resulted in larger exposures to the banking sector. Furthermore, links between insurers and banks are intensified also due to insurers' significant holdings in banks. Baluch et al. (2011) conclude that insurers are exposed to systemic contagion via banks, and banks are susceptible to insurance companies as well due to counterparty risk in the CDS market. They suggest that one should not focus on which sector contributes more to systemic risk, but on the strength of the systemic connection between the two sectors.

Note that the studies of The Geneva Association (2010) and Baluch et al. (2011) are published and sponsored by the insurance industry. Given this, Cummins and Weiss (2014), as an independent third party, have researched on the systemic risk contributions of insurers. By applying the FSB and IAIS criteria to the U.S. insurance sector, they have obtained similar conclusions that some non-core business of the insurance companies may cause systemic risk. They put particular emphasis on reinsurance , a way of risk management where an insurer purchases insurance from one or more other insurers direcltly or through a broker. They suggest that both life and nonlife insurers are vulnerable to reinsurance crises.

The aforementioned research has provided in-depth qualitative analyses, however none of them has quantified systemic risk of insurance companies. In order to measure systemic risk in insurance, Billio et al. (2012) propose Granger-causality networks to assess the connectedness in four sectors–banks, insurers, brokers/dealers and hedge fund. They conclude that all four sectors have become highly interrelated over the past decade. While banks played a much more important role in transmitting shocks than other financial institutions, Billio et al. (2012) note that the connectedness between banking and insurance sectors is more significant than that between other pairs of sectors. This result, together with Baluch et al. (2012), motivate my thesis to highlight the intensity of the inter-links between sectors, especially between banks and insurers.

Another quantitative analysis of systemic relevance in insurance comes from F. Chen et al. (2013). They focus on credit risk insurers (CRIs), which are insurers that supply financial guaranty and write CDS. They have employed two interconnected measures on systemic risk based on equity returns: BANKBETA and marginal expected shortfall (MES). BANKBETA is to divide the covariance of a company's stock return and the banking sector's value-weighted average return by the variance of the banking sector's value-weighted average return, i.e., $\frac{Cov(r_i, r_{banking})}{VAR(r_{banking})}$, where r_i denotes return for firm i and $r_{banking}$ the value-weighted average daily returns of the banking sector. As for MES, proposed by Acharya et al.(2017), it evaluates the worst performance days of individual institutions conditional on the market shortfall. F. Chen et al. (2013) summarise that CRIs are more associated with systemic risk relative to traditional insurers in the 2007-2009 financial crash.

Similar to Billio et al. (2011), H. Chen et al. (2014) performed linear and nonlinear Granger-causality tests to assess the interconnectedness between the insurance and the banking sector. The difference is that H. Chen et al. (2014) have applied both CDS data and equity data into the U.S. market. They find that there is significant bidirectional causality between insurers and banks. Banks, however, cause greater and longer influence on insurers than vice versa after controlling for conditional heteroskedasticity. H. Chen et al. (2014) suggest that their results are attributed to data sources, CDS and equity data, rather than the methodologies they use to examine systemic risk.

Bernal, Gnabo, and Guilmin (2014) have examined the contributions of three financial sectors–banking, insurers and other financial services industries–to systemic risk by using $\Delta CoVaR$ and Kolmogotov–Smirnov test. Their conclusions vary depending on the markets to which the financial institutions belong. Bernal et al. (2014) note that in the Eurozone, other financial services sector contributes the most to systemic risk, with banks being the next highest contributors and insurers the last. In contrast, the insurance industry is the top systemically risky sector in U.S., with the banking industry as the least risky one. Berdin and Sottocornola (2015) have also employed $\Delta CoVaR$ to evaluate the systemic relevance in European insurers. Two other equity return-based measures, linear Granger-causality test and marginal expected shortfall (MES) were employed in addition to $\Delta CoVaR$. They also conclude that insurance companies are systemically relevant, but they are not the main risk contributors relative to the banking sector. They propose that diversification and size could be the driver of systemic risk. However, they have confined their analysis to Europe only.

Although more aforementioned literature has shown the subdominant role of insurers in contributing to systemic risk, Bernal et al. (2014) proposes an opposite view that systemic risk of the insurance industry is higher than that of the banking sector in the US. The mixed results motivate this thesis to further investigate whether insurers are more systemic relevant than banks and NFIs by using multiple leading systemic risk measures. In addition, this thesis has also compared the firm-level risk of banks, insurers and NFIs by employing the most widely accepted firm-level risk measures, the results of which together with systemic risk outcomes produce a more comprehensive risk profile of insurance companies. What's more, as mentioned in Section 3.1, sector risk analyses using CDS data that reflects credit risk, are compared with those using non-CDS data. Finally, inspired by Baluch et al. (2011), this thesis quantifies the connections between sectors through a pairwise analysis.

2.3 The Comparison between Firm-Level Risk and Systemic Risk

Since the last financial crash, regulations were suggested to transfer their attentions from microprudential to macroprudential policies. This section reviews the relationship between firm-level risk and systemic risk. The reviewed papers have proposed their findings by focusing on one common factor that influences both individual and systemic dimensions of risk:

Acharya (2009) proposes an aggregate risk-shifting incentive where banks incline to hold correlated assets, which leads to systemic risk. He points out that regulations based only on bank's individual risk might exacerbate systemic risk and recommends regulating financial institutions by combining both correlated risks and firm-specific risks. His study implies the inequality of a bank's individual risk and its systemic relevance as a part of the financial system as a whole.

Similar to Acharya (2009), Wagner (2010) also focuses on risk-taking behaviours and proposes 'diversification' as the cause of the trade-off between firm-level risk and systemic risk. He confirms diversification as an appropriate strategy to remove idiosyncratic risk by spreading risks across financial institutions, however he also believes it could contribute to systemic crises when firms implement homogeneous risk-takings through diversification. Wagner (2010) therefore suggests lower degree of diversification as optimal, and the regulators should impose high capital requirements on banks associated with more diversified portfolios. Nevertheless, his research has not achieved the ideal level of diversification. Wagner (2010) also notes that the rationale coming from diversification could be extended to financial integration that also facilitates the building of systemic failures.

Different from the previous two studies, López-Espinosa et al. (2013) concentrates on firm characteristics effects rather than risk-taking behaviour effects on individual solvency risk and systemic risk. They evaluate systemic risk using$\Delta CoVaR$, and estimate firm solvency risk by credit default swap spread and the KMV-Merton probability of default. Applying their studies on global financial institutions from 2001 to 2010, López-Espinosa et al. (2013) find that unstable funding sources result in increases of both institution-level risk and the spillover risk, while the trading activities and the liquidity management strategy have opposite effects onn individual risk and systemic risk. López-Espinosa et al. (2013) agree with Acharya (2009), and advocate regulating aggregate risk in addition to company's solvency risk.

Emphasising on the connections between bank competition and bank risks, Leroy and Lucotte (2017) differentiated risk types by using Z-score and distance-to-default to represent individual risk, and SRISK to capture systemic risk. Researching on the European listed banks from 2004 to 2013, Leroy and Lucotte (2017) find that competition stimulates banks to undertake more individual risks, while there is a negative relationship between competition and systemic risk. Strong competition contributes to financial stability as it avoids the high degree of correlated risk-takings. Leroy and Lucotte (2017) therefore suggest a sound competition policy to balance the two categories of banking fragility.

In sum, the existing studies has compared firm-level risk and systemic risk from diverse angles, but they all suggest that regulators should consider both of the two categories of risk in supervising financial institutions. This is one of the reasons that this thesis includes firm-level risk measures in addition to systemic risk measures for sector risk analysis and data type comparisons in risk estimations.

2.4 Comparison between Systemic Risk Measures and Empirical Validation of Them

Bisias et al. (2012) conduct a survey on 31 quantitative systemic risk methodologies. They have compared and summarised all 31 metrics from the aspect of supervisory scope, event-/decision-time horizon, and research method. Supervisory taxonomy classifies systemic analytics into two main categories–micro-prudential and macro-prudential. Event-/decision-time horizon groups the systemic risk methodologies as ex ante measures, contemporaneous measures and ex post measures. Research taxonomy categories all the 31 methods based on the origin of systemic events they capture–liquidity, leverage, losses and linkages, the four L's of financial crisis. According to this criterion, there are probability-distribution measures, contingent claims and default measures, illiquidity measures, network analysis measures and macroeconomic measures. In addition, Bisias et al. (2012) have described inputs, outputs and data requirements in details for each of the 31 systemic risk measures in appendices. Their survey is aiming to facilitate experimentation and innovation in systemic risk analytics, and they suggest that an appropriate risk measure the regulator chooses should capture systemic risk from diverse perspectives due to the complexity of the financial system.

Benoit et al.(2016) have reviewed a broad range of literature on systemic risk to explore relationships between theories, empirical measures and regulatory reforms. During the survey on systemic risk, they group systemic risk approaches into two main approaches–one looks at distinct sources of systemic risk and the other one uses market data to generate global measures. They focus on matching sources of systemic risk, existing regulation, econometric modelling tools and assessments of these tools. Benoit et al. (2016) propose that a more structural model that translates risk indicators to clear policy objectives and effective supervisory tools will be helpful for regulators. They also suggest that future systemic risk metrics should encompass multi-sources of information, including both public and non-public data, and should provide a straightforward systemic risk tax or capital surcharge on systemic important financial institutions (SIFI) for supervisory purpose.

Arsov et al. (2013) have investigated the ability of 11 systemic risk measures[16] to provide early warning signals of crisis by researching on financial institutions in both US and euro area. They have constructed a coincident indicator of stress – systemic financial stress index (SFS) to represent actual stressful events. SFS is computed as the percentage of the amount of the financial institutions that are undergoing large negative abnormal returns. Extreme SFS is a binary variable that takes value of 1 if SFS is greater than or equal to 0.25, and zero otherwise. In order to learn the performance of the 11 risk indicators in signaling stress, Arsov et al. (2013) have employed three methods: (1) Granger causality tests[17], (2) predicting extreme events[18], and (3) Quandt-Andrews break point (QABP) test. They find that different systemic risk metrics work well in distinct tests, and conclude that academics or regulators should select the risk indicator that is consistent with their specific purpose. Rodríguez-Moreno and Peña (2013) have compared the performance of a series of market-based systemic risk measures based on three criteria: (1) correlation of the measures with an index of systemic risk events and policy actions, (2) Granger-causality tests, and (3) Gonzalo and Granger (GG) metric. Their study is reviewed in more details in Section 3.1.1.

Bisias et al. (2012) and Benoit et al. (2016) haven't suggested any one or a few risk metrics

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[16] The 11 systemic risk measures include yield curve slope, time-varying conditional value-at-risk (CoVaR), rolling CoVaR, joint probability of distress (JPoD), Credit Suisse Fear Barometer, distance to default, Diebold-Yimaz, VIX, LIBOR-overnight indexed swap (OIS) spread, systemic liquidity risk indicator (SLRI) and systemic contingent claims approach (CCA).

[17] This is to test whether the 11 systemic risk indicators Granger cause the SFS at diverse lag-lengths.

[18] This is to use logit regressions to check whether 11 systemic risk indicators are able to predict extreme events, i.e., the extreme SFS.

to be better than others, while Arsov et al. (2013) and Rodríguez-Moreno and Peña (2013) have concluded distinct best-performed risk indicators. This thesis tests the predictive power of all the most cited risk measures for the subprime mortgage crisis and comes up with the superior risk methodology based on its forecasting performance. Except Benoit et al. (2016), all other studies have not investigated a leading systemic risk method–SRISK, which will be analysed in this research. In addition, this thesis also clearly differentiates and includes systemic importance and systemic vulnerability of a company in predictive tests.

3 Firm-Level Risk Assessment

Recall that most of the existing studies attribute less systemic relevance to insurers. However, given that high individual instability of a company may result in low systemic relevance of the firm, this section evaluates firm-level risks of banks, insurers and NFIs in addition to systemic risk assessments in Section 4 to provide a manifold risk comparison between sectors.

The firm-level risk measures adopted in this chapter include volatility, Value at risk (VaR), expected shortfall (ES), beta, CDS spread, and Z-Score. These firm-level risk measures are selected because of the following reasons: First, volatility, VaR, and ES are included because they are most widely accepted firm-level risk measures and are selected and discussed in detail in Danielsson (2011). Second, firm-level risk measures are chosen to be comparable with systemic risk measures in Chapter 4. Specifically, VaR is chosen to be related to ΔCoVaR, and beta is selected because it is linked to SRISK (Benoit et al. 2013). Third, this thesis would like to compare results of risk measures using different types of data, thus CDS spread and the well-known accounting data-based Z-Score are added to examine how their results distinct from those of equity-based risk measures (volatility, VaR, ES, beta). Below are the summarised advantages and disadvantages of the selected firm-level risk measures.

Volatility

Volatility, computed as the standard deviation of returns, is the most widely applied measure of risk. It denotes the uncertainty about the movement scope of an asset's value. A higher (lower) volatility means that the value of an asset fluctuates (does not fluctuate) considerably, which represents a higher (lower) risk. Despite the popularity of volatility in risk analysis, conclusions based on variance are only valid when returns follow normal distribution. An example to demonstrate this would be that same values of mean and standard deviation could be acquired from distinct distributions. Therefore, volatility may give the same magnitude to the risk levels of two assets that are actually associated with totally different risk levels.

VaR

Being independent of the underlying distribution, Value-at-Risk (VaR) overcomes the shortcoming of volatility as demonstrated above. VaR (α) is defined as a loss threshold such that the probability of losses over a given time period equaling or exceeding this loss level is α. Particularly, a firm or an asset with a 5% one-month VaR of 3.5% means that there is 5% possibility that the value of the firm or the asset will fall by 3.5% during the one-month time. The majority of financial institutions and regulators assess risk using VaR or methodologies based on VaR. However, there are disadvantages associated with it: VaR is only a quantile that captures the minimum sufferable losses on the return distribution, and it cannot reflect the shape of tail distribution; VaR is easy to manipulate by employing trading strategies. (A bank could increase downside risk so as to lower its VaR by the use of put options. See Example 2 in page 1290 from Daníelsson (2002))

Expected Shortfall

Expected shortfall (ES), also known as tail VaR or conditional VaR, is a risk measure that addresses the issues of VaR by capturing tail distribution. ES refers to the expected loss when losses exceed VaR. ES is superior to VaR as it provides information of the tail shape of distribution. Considering this, Basel III has replaced VaR by ES for risk management purpose (Basel Committee on Banking Supervision 2013b). However, ES also has its problems. Adopting Monte Carlo simulation methods, Yamai and Yoshiba (2005) find that the estimation error, measured by relative standard deviation[19], of ES is higher than that of VaR if the underlying loss distribution is fat-tailed. According to Yamai and Yoshiba (2002), backtesting of ES compares the estimated ES with the mean value of realised losses exceeding VaR, however realised losses beyond VaR are infrequent, so it is difficult to obtain an accurate average value. They therefore conclude that ES is difficult to be applied into backtesting method.

Beta

Beta is a firm-level risk measure to assess whether a company or an investment is more or less sensitive to the market as a whole. The higher the beta, the higher sensitivity of an asset to the variability of the market movements. On one hand, beta quantifies systematic risk, which is not considered in other firm-level risk measures. Besides, beta is simple and easy to use. On the other hand, however, beta is based on the capital asset pricing model (CAPM), which has drawbacks in its inputs and assumptions. The CAPM assumes investors can borrow and lend at a risk-free rate, which is unrealistic in the real market. Risk-free rate and return on market are approximate inputs in the model, which resulted in questionable results.

CDS spread

CDS spread is a periotic payment that a CDS buyer makes in exchange of the protection against the default risk of an underlying asset or underlying entity from the CDS sellers. CDS spread thus represents the credit risk of reference assets or reference entities in a liquid market, and it is expressed as a percentage of the notional value of the CDS contract. CDS spread is the best

[19] The standard deviation is divided by the average.

in terms of measuring credit risk: CDS spread is superior to the spread between corporate and Treasury bond yields, which will be affected by the choice of the benchmark risk-free rate and encompasses other information rather than credit risk (Jorion and Zhang 2007; Blanco, Brennan and Marsh 2005; Forte and Peña 2009 and Norden and Wagner 2008); CDS spread is more accurate than equity price to quantify credit risk in that a rise in leverage increases credit risk and CDS spread, but may create a wealth transfer to shareholders, which leads to a rise in stock price (Jorion and Zhang, 2007). Giglio (2014) notes that the reason CDS price is better than bond price to measure credit risk is that CDS not only reflects the probability of joint default of bond issuer, but also that of the protection seller. In spite of all the advantages CDS data has, there is criticism on it as well: the liquidity of CDS market will affect credit risk estimations (Segoviano and Goodhart 2009).

Z-Score

Apart from the standard risk measures using equity and CDS data, Z-Score that employs balance sheet data, is considered as well. Z-Score is first grounded by Roy (1952), extended later by Boyd and Graham (1986), and finally represented by Hannan and Hanweck (1988) and Boyd and Runkle (1993). It measures the number of standard deviations by which the decline of returns will deplete equity and trigger a default. Different from some financial ratios that are focusing on specific risks, such as current ratio that indicates liquidity risk, Z-Score is a more comprehensive accounting ratio that is broadly accepted to evaluate the overall bank solvency. The higher the Z-Score, the healthier the financial institution is. The traditional calculation assumes ROA is normally distributed, in reality however, financial time series like returns are usually nonstationary, which results in inaccurate estimation results.

The remainder of this section is structured as follows: Section 3.1 demonstrates methodology and data; Section 3.2 presents results and discussions of sector risk ranking; Section 3.3 illustrates rank correlations across the firm-level risk measures and across time; Section 3.4 demonstrates results and discussions of structural break tests; Section 3.5 shows the results of firm risk ranking; Section 3.6 concludes.

3.1 Methodology and Data

3.1.1 Methodology

This section demonstrates the empirical estimations of firm-level risk measures adopted in this thesis.

Volatility

Volatility of the sampled institutions is obtained from a Generalised AutoRegressive Conditional Heteroskedasticity (GARCH) (1,1) model as shown below. GARCH(1,1) is chosen because it is simple and best fits financial time series.

$$r_{it} = \mu_i + \sigma_{it}\epsilon_{it}, \qquad \epsilon_{it} \sim N(0,1) \tag{1}$$
$$\sigma_{it}^2 = \omega_i + \alpha_i(\sigma_{it-1}\epsilon_{it-1})^2 + \beta_1\sigma_{it-1}^2 \tag{2}$$

where r_{it} denotes the equity return of firm i at time t, σ_{it} the standard deviation, μ_i the expected return, and ω_i, α_i, β_1 the parameters. Daily return has been obtained from equity prices, and daily volatility of each sample company is achieved from Eq.1. and Eq.2. Following this, quarterly results are acquired by taking the average values of daily volatility.

VaR

According to the aforementioned definition, VaR is expressed as:

$$Pr(r_{it} \leq -VaR_{it}(\alpha)) \ = \alpha \tag{3}$$

Where VaR_{it} refers to the value of risk of firm i at time t, and α is 0.05. This thesis employs quantile estimation on daily equity price to obtain quarterly values of VaR for each sample company.

Expected Shortfall

ES is defined as the expected loss when losses exceed VaR:

$$ES_{it} = -E_{t-1}(r_{it}|r_{it} \leq -VaR_{it}(\alpha)) \tag{4}$$

Following Eq.3 and Eq.4, quarterly VaR is computed first, and quarterly ES is obtained by taking the average of all returns that are no greater than the quarterly VaR.

Beta

Beta is computed according to Eq.5:

$$\beta_{it} = \frac{Cov(r_{it}, r_{mt})}{Var(r_{mt})} \tag{5}$$

where r_{mt} denotes the market return. $Cov(r_{it}, r_{mt})$ and $Var(r_{mt})$ are obtained from Dynamic Conditional Correlation (DCC) model (Engle 2002): denote $\epsilon_{it} = r_{it}/\sigma_{it}$ and $\epsilon_{mt} = r_{mt}/\sigma_{mt}$ the volatility adjusted returns for r_{it} and r_{mt} respectively. The DCC correlations are thus:

$$Cor\begin{bmatrix}\epsilon_{it}\\ \epsilon_{mt}\end{bmatrix} \ = \ R_t = \begin{bmatrix}1 & \rho_{it}\\ \rho_{it} & 1\end{bmatrix} = diag(Q_{it})^{-1/2}Q_{it}diag(Q_{it})^{-1/2} \tag{6}$$

where Q_{it} is the pseudo correlation matrix and its dynamics are specified as:

$$Q_{it} = (1-\alpha-\beta)S_i \ + \alpha\begin{bmatrix}\epsilon_{it-1}\\ \epsilon_{mt-1}\end{bmatrix}\begin{bmatrix}\epsilon_{it-1}\\ \epsilon_{mt-1}\end{bmatrix}' + \beta Q_{it-1} \tag{7}$$

where S_i is the unconditional correlation matrix of ϵ_{it} and ϵ_{mt}. In this thesis, the daily variance of company returns, and the covariance of company and market returns are achieved from Eq.6. Following this, quarterly variances and covariances are obtained using the mean values of daily ones. Finally, values of beta are the results from Eq.5.

CDS spread

CDS spread is the daily data of 5-year CDS contracts retrieved from Datastream. 5-year maturity is chosen because it is the most liquid type of contract.

Z-Score

Z-Score is defined as the inequality below:

$$Pr(ROA \leq -EA) \leq Z^2 \tag{8}$$

$$Z \equiv \frac{EA+\mu(ROA)}{\sigma(ROA)} \tag{9}$$

where ROA denotes the return on asset, $\mu(ROA)$ and $\sigma(ROA)$ the mean and standard deviation of ROA respectively, EA the total equity over asset, and Z the Z-Score. Eq.8 and Eq.9 assume that ROA is normally distributed, however ROAs are normally nonstationary, so this thesis follows the Algorithm 1 in Mare et al. (2016) to estimate Z-Score by considering nonstationary ROA. Specifically, the first step is to fit a trend line $f\ (y) = a + by$ to ROA realisations for each rolling time window. Compute the central value of each trend line and detrend ROA realisations by restoring the differences between ROA realisations and the corresponding central values of certain trend lines (line 5 in Table 2). Then estimate $\bar{\tau}$ using the mean value of the central values of the trend lines and the detrended ROA realisations (line7,8,9 in Table 2). The forecasted average ROA values in time t is f(t), and $\bar{\tau}f(t)$ is ROA standard deviation when $\bar{\tau}f(t)$ is big enough, otherwise ROA standard deviation will be obtained from the bias adjusted sample standard deviation $\bar{s}$ (line 13 in Table 2).

Table 2 Z-Score Computation for Nonstationary ROA

Algorithm: computing Z_7^k

Data: denote r an array of ROA realisations; t the period to estimate the Z-Score; EA equity over asset at time t; k the time window (in periods) used for trend estimation, an odd number greater than one.

Result: z the estimated Z-Score at period t

$n = t - k - 1; d = \{\}; x = \{\}; k = 1;$

for $i \leq n + 1$ **do**

  fit a trend line $f\ (y) = a + by$ to the time series $r_i, \dots, r_{i+k-1}$;

  $x = x \cup \{f(i + (k-1)/2)\}$;

  $d = d \cup \{r_{i+(k-1)/2} - f(i + (k-1)/2)\}$;

end

$m = mean(x)$;

$s = standard\ deviation\ (d)$;

$\bar{\tau} = (1 + 1/(4(\mathrm{n} + 1)))\mathrm{s}/\mathrm{m}$;

if $|\bar{\tau} f(t)| \leq \epsilon$ **then**

  standard deviation forecast very close to zero, i.e., smaller than ϵ;

  $\bar{s} = s\bar{\chi}(n + 1)/\sqrt{n}$;

  $z = -(EA + f(t))/\bar{s}$;

else

  $z = -(EA + f(t))/(\bar{\tau} f(t))$;

end

By comparing the sector risk analyses of the firm-level risk measures using various data, the first hypothesis that this section attempts to test is as below.

H3.1: Sector risk ranking varies depending upon the particular data type that a firm-level risk is based on.

Considering that Standard & Poor's employs CDS as early risk warning signals of outliers that may require imperative review, this section tests the second hypothesis below by comparing the results of CDS spread with those of other data-based risk measures, as well as by testing structural breaks of the firm-level risk measures.

H3.2: CDS spread provides early risk signals than equity-based and accounting-based firm-level risk metrics.

3.1.2 Data

All data in this thesis – equity prices, CDS spread, market values, book value of assets, book value of equity, book value of debt, are retrieved from Datastream. Among them, equity prices, CDS spread, and market values are daily data ranging from 3/1/2005 to 31/12/2014, while book value of assets, book value of equity, and book value of debt are quarterly data from Q1 2005 and Q4 2014. 2005 is the earliest time to be included in a pre-crisis analysis in that CDS data is only available since 2005. In addition, this thesis focuses on risk level changes between the pre-crisis period and crisis period, therefore the post-crisis period in this thesis do not include the latest years and ends in 2014. Companies are classified according to Standard Industrial Classification (SIC) codes: 6000-6199 (banks), and 6300 to 6499 (insurers). Non-financial institutions are selected from the non-financial compositions of S&P 500 by market value. Due to the limitation of CDS data, and in order to achieve an equal company number within each industry, sample size in this thesis is 96, with 32 banks, 32 insurers, and 32 non-financial institutions. In each industry, companies are selected depending on whether they have valid CDS data, on top of which only the largest companies (measured by market value) are included. Data requirements for the firm-level risk measures employed in this thesis are listed in Table 3, where $EA = \frac{Quarterly\ Book\ Equity}{Quarterly\ Total\ Asset}$ and $ROA = \frac{Quarterly\ Return}{Quarterly\ Total\ Asset}$.

Table 3 Data Requirements of Firm-Level Risk Measures

Firm-level risk measures	Data	Data type	Frequency	Sample
Volatility	Equity return	Market	Daily	3/1/2005–31/12/2014
VaR	Equity return	Market	Daily	3/1/2005–31/12/2014
Expected Shortfall	Equity return	Market	Daily	3/1/2005–31/12/2014
Beta	Equity return, market return	Market	Daily	3/1/2005–31/12/2014
CDS spread	CDS spread	Market	Daily	3/1/2005–31/12/2014
Z-Score	EA, ROA	Accounting	Quarterly	2005 Q1 – 2014 Q4

Source: Datastream

Both the aforementioned firm-level risk measures and the systemic risk measures in Section 4 are applied to banks, insurers and non-financial institutions (NFIs) across regions including U.S., Europe and Asia. Due to the limitation of CDS data, sample size is confined to 96 companies with each industry comprising 32 firms. However, all the companies in each sector are selected from the S&P 500 index components in a descending order by market capitalisation, and thus they are the largest ones on which CDS contracts are written in a specific industry. The list of the 96 companies is presented in Appendix 1. If a company has subsidiaries, only the holding company is selected, assuming that the risk level of a parent corporation affects and represents the instability of its subsidiaries.

Appendices from Appendix 2 to Appendix 5 have described the statistics of CDS spread and equity returns by company and by sector respectively. Sample period spans from 3rd January 2005 to 31st December 2014, thus there are 2608 CDS observations and 2607 equity returns for each institution. In Appendix 2, firms with maximum CDS values exceeding 1000 are in bold: AIG, Legal & General, Lincoln National, MBIA, MGIC, Metlife, Morgan Stanley, Old Mutual, Radian Group and The Hartford. On the other hand, companies are highlighted with minimum equity returns lower than -0.39 in Appendix 4: AIG, Aviva, CNA Financial, Citigroup, Lincoln National, Lloyds Banking Group, MBIA, MGIC, RBS and The Hartford. Appendix 3 shows that the insurance sector is the riskiest sector with the highest CDS spreads in terms of mean, standard deviation and maximum values. In Appendix 5, the banking industry is associated with the largest losses with the lowest mean and minimum value of equity returns, while the equity returns of insurance companies are volatile the most indicated by standard deviation. Appendix 6 and Appendix 7 have presented the statistical descriptions of equity over asset (EA) and return on asset (ROA). Since EA and ROA are computed from balance sheet data, they are on quarterly basis with sample period ranging from 2005 Q1 to 2014 Q4, i.e. 40 observations. In terms of mean values in Appendix 6 and Appendix 7, both EA and ROA of NFIs are higher than those numbers of insurers and banks.

3.2 Sector Risk Ranking

Before ranking risk levels among banks, insurers, and NFIs using Conover-Iman tests, this section has done multiple statistical significance tests to examine whether results from the firm-level risk estimations are statistically different from zero and whether the selected firm-level risk measures are statistically different from each other.

3.2.1 One-Sample Wilcoxon Signed-Rank Test

This thesis employs the one-sample Wilcoxon signed-rank test to assess whether the risk results are significantly different from zero. The one-sample Wilcoxon signed-rank test is chosen because it is a non-parametric alternative to one-sample t test, and it does not require data to follow a normal distribution. Specifically, the one-sample Wilcoxon signed-rank test is implemented on each of the 96 company time series for each of the firm-level risk measure. The null hypothesis is that the tested data come from a distribution whose median is zero. Appendix 8 has shown the one-sample Wilcoxon signed-rank test results for firm-level risk measures.

3.2.2 Kruskal-Wallis Test

This section checks whether firm-level risk results from one risk measure are statistically different from another. This thesis adopts the Kruskal-Wallis test, a non-parametric method that does not assume normal distribution of data, to test whether samples originate from the same distribution. Besides, since there are more than two firm-level risk measures to compare (6 in total), Kruskal-Wallis test is the most appropriate method to compare two or more independent samples.

Since firm-level risk results are panel data with 40 quarters and 96 companies, this section first performs one Kruskal-Wallis test on the 6 firm-level risk measures by using the time series data of the first company. Then this has been repeated for all the remaining 95 companies in the sample. That is to say, there are 96 test results based on each of the sample company. The null hypothesis of the test is that all samples come from the same distribution, while the alternative hypothesis is that not all samples are from the same distribution.

Appendix 9 shows the comparison results from the Kruskal-Wallis for firm-level risk measures. As can be seen from the Appendix 9, all Kruskal-Wallis tests have shown that at least one firm-level risk measure is different from at least one other risk measure.

3.2.3 Conover-Iman Test for Sector Risk Ranking

The Kruskal-Wallis test only shows whether samples are different from each other, it does not identify which particular sample dominate which another sample. Therefore, a post hoc test is necessary following the Kruskal-Wallis test. Conover-Iman test is employed in this thesis as the post hoc test as it is a non-parametric test with no assumptions on normal distributions of the sample data, and it is a more powerful test than others by testing differences in both the location parameters (medians) and the scale parameters (statistical dispersion) of the populations.

The Conover-Iman test generates the Conover-Iman t statistic of the rank differences to assess the statistical dominance among multiple pairwise comparisons following a Kruskal-Wallis test on multiple samples. In this thesis, it is a comparison among risks of three sectors – banks, insurers and non-financial institutions (NFIs), and these sector comparisons are implemented on each distinct period – pre-crisis (2005 Q1 to 2007 Q2), crisis (2007 Q3 to 2009 Q2) and post-crisis period (2009 Q3 to 2014 Q4). For each 40×96 matrix (40 quarters and 96 companies) resulted from each firm-level risk measure, sector risk levels are acquired by taking the mean value across companies. After this, all sector risk values are separated into three time periods – the pre-crisis period (2005 Q1 to 2007 Q2, 8 quarterly data), the crisis period (2007 Q3 to 2009 Q2, 10 quarterly data) and the post-crisis period (2009 Q3 to 2014 Q4, 22 quarterly data). For each of these periods, sector risk is compared by using the Conover-Iman test. The null hypothesis is that there is an equal probability that a randomly selected risk value from one sector is greater than the random selected risk value from the other sector. The alternative hypothesis is then that the risk of one sector statistically dominate the other one.

Appendices from Appendix 10 to Appendix 15 have shown the results of the Kruskal-Wallis rank sum test and the Conover-Iman test that compares sector risk for each firm-level risk measure by time. Take "Insurers - Banks" as an example, it means the rank difference between insurers and banks (i.e. insurers minus banks). A positive (negative) t statistic means that insurers are riskier (less risky) than banks[20] and adjusted P values in brackets is for inferring statistical significance. As can be seen from the appendices, the results on volatility, VaR, ES, and beta have shown that both insurers and banks are significantly riskier than NFIs during the crisis time and the post-crisis time. One result in beta different from the other three measures is that the two pairs of Insurers - NFIs, and Banks - NFIs are also significant in the pre-crisis time. Test results on CDS spread generally show that insurers are associated with higher credit risk than banks and NFIs throughout the whole sample periods. As for Z-Score, all three pairwise comparisons (Insurers – Banks, Insurers – NFIs, Banks – NFIs) are significant in all periods.

3.2.4 Conover-Iman Test for Time Periods Risk Comparison

This thesis has also compared risk among three time periods – pre-crisis (2005 Q1 to 2007 Q2), crisis (2007 Q3 to 2009 Q2) and post-crisis period (2009 Q3 to 2014 Q4). For one resulted 40×96 matrix (40 quarters and 96 companies), the risk level of one company in a particular period is achieved by taking the mean value across the relevant quarterly values of this company. These risk values for each time period are grouped by sectors. For each sector, risk rankings of three time periods are performed by the Conover-Iman test. The null hypothesis for each pairwise comparison is that there is an equal chance that a randomly selected risk value from one risk period is higher than the random selected risk value from another time period. The alternative hypothesis is then that the risk of one time period significantly dominate the other one.

Appendices from Appendix 16 to Appendix 21 have shown the outcome of the Kruskal-Wallis rank sum test and the Conover-Iman test that compare risk among the pre-crisis period, crisis period, and post-crisis period by sector. The pair of "Crisis – Pre-crisis" represents the risk rank difference between the crisis period and the pre-crisis period (i.e. crisis minus pre-crisis). A positive (negative) t statistic suggests that risk in the crisis period is higher (lower)

[20] It is opposite relationship for Z-Score: a positive (negative) t statistic means that insurers are less risky (riskier) than banks.

than that of the pre-crisis period[21]. Adjusted P values are in brackets is. According to these appendices, all firm-level risk measures for all three sectors have generally achieved an agreement that the crisis period is riskier than the pre-crisis period. Except beta and CDS spread, basically all other risk measures suggest that the crisis period is associated with greater risk than the post-crisis period. These findings are consistent with the evidence from the subprime mortgage crisis.

3.3 Rank Correlations across the Firm-Level Risk Measures and across Time

3.3.1 Rank Correlations across the Firm-Level Risk Measures

Following Brownlees and Engle (2016), this thesis employs Spearman's ρ, the rank correlation method, to measure the non-linear correlation of the firm-level risk results across risk measures and across time.

Since the firm-level risk results are in panel patterns, rank correlation across risk measures in this research is performed on both time series and cross-sectional data. Rank correlation using time series data is to obtain quarterly data for one risk measure by taking average across companies for each quarter, and correlate one risk measure's quarterly time series with those from one other risk method. Rank correlation using cross-sectional data is to take average across quarters for each company and correlate the cross-sectional data of each risk measure with that of each of the other risk methodology.

Appendix 22 and Appendix 23 present the results of rank correlations across the firm-level risk measures using time series and cross-sectional data respectively. It has shown that all pairwise firm-level risk measures are significantly correlated, with positive correlations among volatility, VaR, ES, beta and CDS, while negative correlations between Z-Score and each of the other risk method. This is because Z-Score is the only risk measure that is negatively associated with risk levels, whilst values of other methods increase as risk rises. More specifically, on one hand, volatility, VaR and ES are strongly correlated, with their figures of Spearman's ρ no lower than 0.97. On the other hand, pairs involving beta or CDS indicate slightly lower correlation values, with Z-Score presenting the lowest level of association with others. Given the aforementioned observations and considering that volatility, VaR and ES are computed from equity returns, beta involves both company and market returns, CDS is the 5-year CDS spread, and Z-Score is built on accounting data, this may suggest that risk results are affected by the underlying data that a particular risk method is based on.

[21] It is opposite relationship for Z-Score: a positive (negative) t statistic means that risk of the crisis period is lower (higher) than that of the pre-crisis period.

3.3.2 Rank Correlations across Time by Firm-Level Risk Measures

Rank correlation across time is to correlate risk levels among pre-crisis, crisis, and post-crisis period for each of the firm-level risk measure. Pre-crisis period ranges from 2005 Q1 to 2007 Q2, crisis period includes quarters from 2007 Q3 to 2009 Q2, and post-crisis period spans from 2009 Q3 to 2014 Q4.

Appendix 24 exhibits the outcomes of rank correlations across time for each of the firm-level risk measure. According to Appendix, all Spearman's correlations are statistically significant. Speaking of volatility, VaR, ES and beta, all of which are based on equity data, the highest correlation is between crisis and post-crisis (with Spearman's correlations no smaller than 0.775). Pre-crisis is slightly more correlated with post-crisis than with crisis. This may suggest that the subprime mortgage crisis has a prolonged effect on the post-crisis period, and the pre-crisis period is a relatively tranquil period. In terms of CDS, the pair of crisis and post-crisis also shows the highest value of Spearman's correlation than the other two pairs. However, different from the equity-based risk measures, CDS indicates that pre-crisis correlates more with crisis than with post-crisis. As for Z-Score, all three pairwise periods present small differences in levels of rank correlations.

3.4 Structural Break Tests

Through the Conover-Iman test, this thesis has ranked risk magnitude among banks, insurers and NFIs. After this, this section would like to investigate risk change timing among the three sectors by comparing the dates of their risk turning points using structural break tests. Meanwhile, the structural break test aims to identify which data type provides earlier risk signal.

Following Arsov et al. (2013), autoregressive regressions and Quandt-Andrews break point (QABP) tests are performed to examine an unknown structural break point of each firm-level risk metric by sector. A break date obtained from one test is the time point when the risk of a firm, indicated by one risk measure, transformed from being in a peaceful mode to a volatile status. For each risk method, frequencies of all significant break dates obtained from the 96 tests are grouped by sector, as demonstrated in **Error! Reference source not found.**.

According to **Error! Reference source not found.**, companies in each firm-level risk methodology have shown various break points, which implies that a shock may affect market participants at different levels. If the break date with the highest frequency (the highest bar in the plot) represents the turning point of one metric, as can be seen from **Error! Reference source not found.**, the turning points are 2008 Q3 for volatility, 2009 Q1 for VaR, 2008 Q3 for expected shortfall, 2009 Q1 for beta, 2011 Q4 for CDS spread, and 2008 Q3 and 2008 Q4 for Z-Score. According to the sector composition of the highest bar in each of the six sub-plots, more banks experienced a structural change than insurers and NFIs. Comparing the dates of the highest bars in the six sub-plots, volatility and expected shortfall provide roughly earlier risk signals than other risk metrics. However, if focus on the earliest significant break quarter (the first bar) for each of the six risk evaluations, the turning points are 2007 Q4 for volatility, 2008 Q3 for VaR, 2008 Q3 for expected shortfall, 2008 Q3 for beta, 2007 Q4 for CDS spread and 2008 Q3 for Z-Score. In terms of the sector composition of the first bar in each of the six sub-plots, roughly more insurers[22] transformed their risk modes relative to the other two sectors. Comparing the earliest significant turning dates of the six risk measures, volatility and CDS spread altered their risk status in the same earlier quarter, while all others moved to volatile modes later when Lehman Brother filed bankruptcy. Although volatility and CDS spread have shown the same earliest break point in 2007 Q4, the number of companies that changed structures in this quarter is higher indicated by CDS than by volatility. In other words, CDS delivers relatively earlier signals than equity- and accounting-based risk indicators.

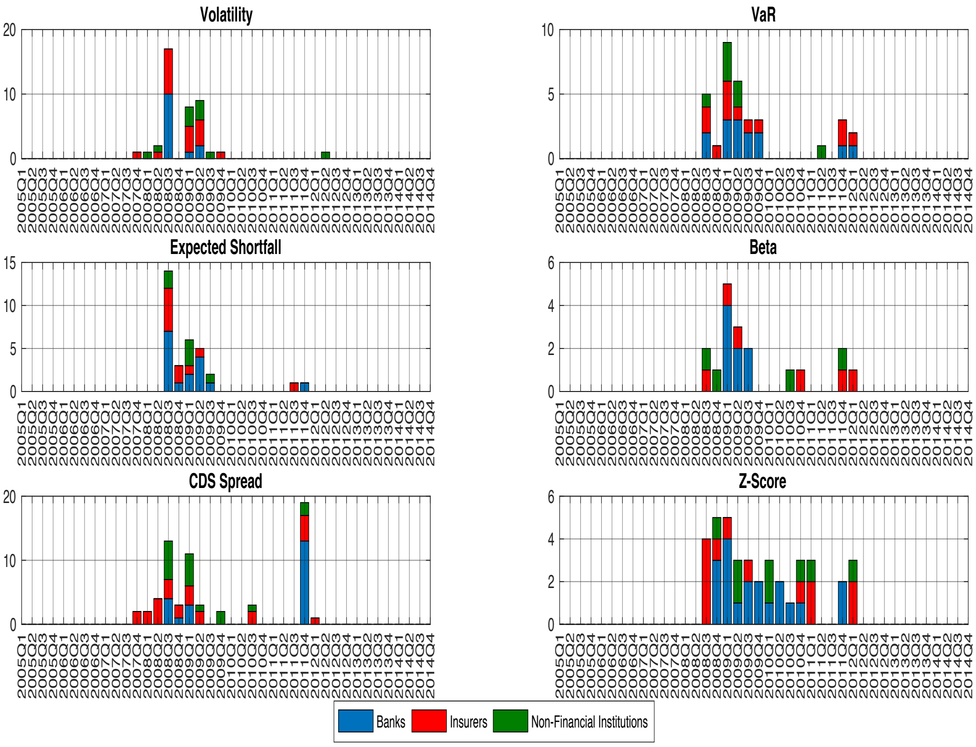

Figure 7 Frequencies of All Significant Break Points for Each of the Firm-Level Risk Measures

The figure presents the frequencies of all significant structural break dates, grouped by industry, for every firm-level risk method–volatility, VaR, expected shortfall, beta, CDS spread and Z-Score. Break points for each risk method are obtained by the autoregressive regressions of the 96 firms in the sample and the Quandt-Andrews break point (QABP) tests on the regressions.

[22] Exceptions: same number of insurers changed risk mode to that of banks (VaR), to that of NFIs (Beta), and more banks than insurers experienced the break (expected shortfall)

3.5 Company Risk Ranking

Risk levels of the sampled institutions are ranked in a descending order according to the firm-level risk estimations. Appedices from Appendix 25 to Appendix 30 have listed the risk ranked companies[23] indicated by each of the six firm-level risk metrics respectively from 2007 Q3 to 2009 Q2, the crisis period.

In Table 25, volatility recognises MBIA and AIG, both of which collapsed during the subprime mortgage crisis, as riskiest companies with higher degree of return variations. In 2008 Q4 and 2009 Q1, The Hartford and Citigroup come in the first place respectively. Both of them experienced higher average equity losses compared with other firms as shown in Appendix 4. Moreover, Radian Group and MGIC (Mortgage Guaranty Insurance Corporation) are another two companies that have the most volatile equity returns in most of the selected quarters. Associated with mortgage insurance, Radian Group and MGIC were hit hard in the subprime mortgage crisis, which also leads to the discard of the merger between them in August 2007. The top three risky companies presented in Appendices from Appendix 26 to Appendix 29 have a large overlap with those ranked by volatility. Details are presented as below.

In Appendix 26, VaR, computed as the 95th percentile, has shown the higher risk levels of MBIA, AIG, Radian Group, MGIC, and The Hartford, which are the same companies as suggested by volatility. On top of this, VaR also identifies two additional financial institutions in 2009 Q1 and 2009 Q2 – Lloyds Banking Group and KBC Bank, both of which received funding from the TARP in the U.S., and bailouts from the UK government and Belgian government respectively as well.

Expected shortfall in Appendix 27, unsurprisingly, has shown company risk rankings consistent to VaR. However, there are two differences in the ranking results between VaR and expected shortfall. In contrast to VaR, expected shortfall shows that MBIA rather than Radian Group is the riskiest firm in 2008 Q2, and Royal Bank of Scotland (RBS) instead of Lloyds Banking Group is at the first place in 2009 Q1. This implies that the tail of the return distribution for MBIA/RBS is associated with more negative returns than that for Radian Group/Lloyds Banking Group, which although has a lower sufferable loss measured by the 95th quantile of its return distribution. Apart from the same aforementioned firms highlighted by volatility, VaR and expected shortfall, Appendix 28, listing companies ranked by beta, adds Morgan Stanley as the second risky firm in 2008 Q4. Take Morgan Stanley as an example, its higher risk indicated by beta means that the equity return changes of Morgan Stanley are more

[23] Only the top 20 of the rank list are shown in the appendices

sensitive to market return movements, i.e., it is with higher systematic risk. Morgan Stanley is said to raise the most capital, $107.3 billion, from the Fed during the crisis relative to other banks.

In Appendix 29, MBIA, Radian Group and AIG are more frequently ranked as top three risky institutions indicated by CDS spread. MBIA and Radian Group were providing substantial credit enhancement through financial guarantees on mortgage-backed securities, and AIG was one of the major CDS issuers prior to the financial crash. All of them were thus heavily exposed to credit risk and were hit hard in the subprime mortgage crisis. In Appendix 30, however, Z-Score using accounting data has listed distinct risky firms from other measures with more NFIs ranked in higher positions. This may be attributed to the nature of Z-Score that captures the general fundamental solvency of a firm rather than any specific risk sources associated with particular shocks. For example, CDS reflects credit risk, while volatility, VaR and expected shortfall measures equity risk, and beta represents systematic risk.

3.6 Conclusions

The empirical results from the Conover-Iman test reveal that risk levels of banks and insurers, resulted from the equity-based risk measures (volatility, VaR, ES, beta), were roughly equal. And both of them were riskier than NFIs during the crisis and post-crisis periods. By contrast, credit risk (CDS spread) of insurers was greater than banks during the pre-crisis and post-crisis periods, and greater than NFIs throughout the sample periods. Furthermore, Z-Score, built on accounting data, agree with the equity-based risk indicators that banks and insurers are risker than NFIs, but it also indicates that insurers are riskier than banks. That is to say, risk ranking among banks, insurers, and NFIs depends on the data type a risk method employs, implying that multiple risk measures to capture diverse directions of risk should be considered in sector risk analysis. This is consistent with the hypothesis H3.1.

The empirical results from the rank correlation complements the Conover-Iman test by showing that data type of a risk method plays an essential role in estimating risk. This comes from the observations that firm-level risk methods using the same data source correlate more with each other, while risk indicators employing distinct data present lower level of correlation.

Outcomes resulted from structural break tests indicate that, generally, risk of insurance companies soared before that of the other two sectors. What’s more, CDS provides slightly earlier warning signals of risk changes than other information-based metrics, which is consistent with the hypothesis of H3.2.

4 Systemic Risk Assessment

This section focuses on market-based systemic risk measures, therefore the most accepted and highly cited market-based systemic risk measures are included： $\Delta CoVaR$ (Adrian and Brunnermeier 2016), Granger-causality tests (Billio et al. 2012), Distress Dependence Matrix(DiDe) (Segoviano and Goodhart 2009) and SRISK (Acharya et al. 2012, Brownlees and Engle 2012). Systemic expected shortfall (SES) (Acharya et al. 2017) and Distress Insurance Premium (DIP) (Huang et al. 2011) are also popular risk measures but not included in this chapter. SES is not chosen because SRISK is similar to and relatively more advanced than SES. DIP is not adopted because it has a similar idea to MES, which is the basis of SRISK, therefore this thesis only selects SRISK. Besides, this thesis focuses on statistical risk measures, therefore structural risk methodologies such as network analysis is not included in this thesis. Last but not least, this thesis is the first one to extend Granger-causality tests to impulse response function (IRF) to evaluate systemic risk by capturing impulses and responses of pairwise companies.

Since this thesis would like to compare results of systemic risk measures using CDS and non-CDS data used in, CDS data is applied into equity-based systemic risk methodologies for comparison. Following this, risk methodologies in this chapter include: $\Delta CoRisk$ (CDS-based $\Delta CoVaR$), $\Delta CoVaR$, CDS-based Granger-causality tests, Equity-based Granger-causality tests, CDS-based IRF, Equity-based IRF, DiDe, LRMES and SRISK.

The remainder of Section 4 is organised as: Section 4.1 demonstrates methodology; Section 4.2 shows results and conclusions of sector connectedness analysis; Section 4.3 discusses the results of sector risk ranking; Section 4.4 performs rank correlations across the systemic risk measures and across time; Section 4.5 presents results of structural break tests; Section 4.6 lists firm risk ranking; Section 4.7 concludes.

4.1 Methodology and Data

4.1.1 Methodology

$\Delta CoVaR$

According to Adrian and Brunnermeier (2016), $\Delta CoVaR$ is defined as the difference of VaR of the financial system (or firm j) conditional on firm *i* in an extreme event and the VaR of the financial system (or firm j) conditional on firm *i* in a median state. This thesis assesses $\Delta CoVaR$ between pairwise companies:

$$\Delta CoVaR_{it}(\alpha) = CoVaR_{it}^{j|r_{it}=VaR_{it}(\alpha)} - CoVaR_{it}^{j|r_{it}=Median(r_{it})} \quad (10)$$

Where $CoVaR_{it}^{j|r_{it}=VaR_{it}(\alpha)}$ denotes the VaR of the firm j conditional on the event when the loss of firm i equals $VaR_{it}(\alpha)$. In addition to quantile regression, $CoVaR$ could also be obtained by Multivariate $GARCH$ model (e.g., Girardi and Tolga Ergün, 2013). This thesis chooses the Multivariate $GARCH$ model because it could reflect the time-varying evolution of systemic risk contributions.

Consider a bivariate GARCH process for the vector of demeaned returns for firm *i* and firm *j*: $r_t' = (r_{jt}\ r_{it})$

$$r_t = H_t^{1/2} v_t \tag{11}$$

where $r_t' = (r_{jt}\ r_{it})$. The vector $v_t{}' = (\epsilon_{jt}\ \xi_{it})$ are the associated standardised innovations and are assumed to be i.i.d., with the first moments as $E(v_t) = 0$ and $E(v_t v_t{}') = I_2$, where I_2 is a two-by-two identity matrix. H_t denotes the variance-covariance matrix:

$$H_t = \begin{pmatrix} \sigma_{jt}^2 & \rho_{it}\sigma_{it}\sigma_{jt} \\ \rho_{it}\sigma_{it}\sigma_{jt} & \sigma_{it}^2 \end{pmatrix} \tag{12}$$

where σ_{it} and σ_{jt} denote the conditional standard deviation of firm i and the firm j, and ρ_{it} denotes the conditional correlation between the firm i and firm *j*. Given Eq.11 and Eq.12, Benoit et al. (2013) have shown that $\Delta CoVaR$ of firm i is proportional to its VaR and the proportionality coefficient is related to the conditional correlations between firm *i* and firm *j* and their volatilities :

$$\Delta CoVaR_{it}(\alpha) = \gamma_{it}[VaR_{it}(\alpha) - VaR_{it}(0.5)] \tag{13}$$

where $\gamma_{it} = \sigma_{it}\sigma_{jt}\rho_{it}/\sigma_{it}{}^2$.

By using Multivariate $GARCH$ model, this thesis first obtains the covariance between the daily equity returns of firm i and firm *j*, and the variance of firm i to obtain the daily γ_{it}. Quarterly γ_{it} *is* computed by taking average of its daily values. Quarterly $VaR_{it}(\alpha)$ and quarterly $VaR_{it}(0.5)$ are achieved by using quantile estimation on the daily equity returns of firm *i* within a corresponding quarter, with α = *0.05* representing the extreme event and 0.5 indicating median state.

Since this thesis would like to compare the results from risk methodologies using different data, this chapter also applies CDS spread into $\Delta CoVaR$, which becomes $\Delta CoRisk$. Daily CDS return is first computed from the CDS data, then both CDS returns of firm i and firm j are applied into the Multivariate $GARCH$ model. Following this, the same calculations for $\Delta CoVaR$ (equity returns) as demonstrated above is implemented as well for $\Delta CoRisk$ (CDS spread).

Granger-causality tests and Impulse Response Function

This research follows Billio et al. (2012) and denote r_{it} and r_{jt} the equity return of firm i and firm j respectively. Assume r_{it} and r_{jt} are two stationary time series and have zero means. The mathematical formulation of Granger-causality test is based on linear regressions of r_{it+1} and r_{jt+1}on r_{it} and r_{jt}, which could be expressed as:

$$r_{it+1} = a_i r_{it} + b_{ij} r_{jt} + e_{it+1} \tag{14}$$

$$r_{jt+1} = a_j r_{jt} + b_{ji} r_{it} + e_{jt+1} \tag{15}$$

where e_{it+1} and e_{jt+1} are two white noise processes and they are uncorrelated, while a_i, a_j, b_{ij}, b_{ji} are coefficients of the regressions. j is said to Granger-cause i when b_{ij} is significantly different from zero, and i Granger-causes j when b_{ji} is significantly different from zero. Both significant granger-causal relationships imply that j (i) encompass information to predict i (j) beyond the information contained in past values of i (j) alone, which means that there is a feedback connection between the two financial institutions. This thesis runs the Vector Autoregression (VAR) model and Granger-causality test on daily equity returns for each of the annual time period from 2005 to 2014. Follows Billio et al. (2012), this thesis adopts GARCH model to control for heteroskedasticity.

Subsequently, this thesis extends the Granger-causality test to impulse response function (IRF). For the pair of $firm_i$-$firm_j$, IRF measures when there is a one standard deviation shock to $firm_j$, what are the maximum value (magnitude, y-axis of the IRF plot) and duration (x-axis of the IRF plot) of the response from $firm_i$ to the impulse. The maximum value and duration for a pair of sectors are the averages of the maximum values and lasting periods for pairwise companies. Higher peak values or longer lasting periods indicate greater systemic risk effects. Given the two dimensions of the IRF results, IRF analysis is thus categorised into two groups: IRF maximum value analysis and IRF lasting period analysis. For IRF maximum value analysis (IRF lasting period analysis), maximum values (lasting periods) resulted from IRFs of pairwise companies for each year are collected. In this research, the Granger-causality tests have been done using the data of daily CDS spread in addition to daily equity returns in order to investigate how data types affect risk estimations. Since CDS data is less liquid in some quarters of 2005 and 2006, Granger-causality test and IRF analyses using CDS data are invalid when running regressions for these quarters, therefore, IRF analyses are on annual basis.

Distress Dependence Matrix

Distress dependence matrix (DiDe) is a matrix presenting conditional probabilities of distress (PoD) between pairwise companies. Therefore, an analysis on pairwise default dependence between companies in the system is necessary. Following Segoviano and Goodhart (2009), for pairwise analysis, suppose there are company X and company Y in the portfolio, whose logarithmic returns are the random variables x and y respectively. The Consistent Information Multivariate Density Optimizing (CIMDO)-objective function to recover the pairwise density is expressed as:

$$\mathrm{C[p,q]} = \iint p(x,y)\ln\left[\frac{p(x,y)}{q(x,y)}\right]dxdy, where\ q(x,y) and\ p(x,y) \in \mathbb{R}^2 \quad (16)$$

where q(x,y) is the prior joint density of x and y in theory, and p(x,y) is the posterior multivariate distribution, i.e., CIMDO-density, which updates with empirical information. The prior distribution q accords with the economic intuition that "default is triggered by a drop in the firm's asset value below a threshold value", and it is consistent with theoretical models such as the Merton model. However, q is not able to capture the empirically observed PoDs of banks. To solve this problem, Segoviano and Goodhart (2009) propose the CIMDO-approach to recover the posterior distribution p that incorporates empirical information. In this thesis, the prior distribution q is obtained from the Bivariate Normal Copula Function (BNCF) as shown below:

$$\mathrm{C(u,v;\rho)} = \int_{-\infty}^{\Phi^{-1}(u)}\int_{-\infty}^{\Phi^{-1}(v)}\frac{1}{2\pi\sqrt{1-\rho^2}}exp\left[-\frac{s^2-2\rho st+t^2}{2(1-\rho^2)}\right]dsdt \qquad (17)$$

where u and v are the marginal distribution of x and y. ρ is the coefficient matrix (2×2). Φ is the standard normal distribution function, while Φ^{-1} represents the inverse function of Φ. The posterior distribution p is then recovered through an optimisation process which makes the prior distribution q update with empirically estimated PoDs via a set of constraints. These constraints are as shown below:

$$\iint p(x,y)\chi_{[x_d^x,\infty)}dxdy = PoD_t^x, \quad \iint p(x,y)\chi_{[x_d^y,\infty)}dydx = PoD_t^y \qquad (18)$$

where $\mathrm{PoD_t^x}$ and $\mathrm{PoD_t^y}$ are the empirical PoDs of x and y estimated from CDS spread at time t[24], and $\chi_{[\mathrm{x_d^x},\infty)}, \chi_{[\mathrm{x_d^y},\infty)}$ are indicating functions that are associated with the thresholds of the default $\mathrm{x_d^x}$ and $\mathrm{x_d^y}$. Additionally, the conditions that $\mathrm{p(x,y)} \geq 0$ and $\iint \mathrm{p(x,y)dxdy} = 1$ should apply to guarantee that $\mathrm{p(x,y)}$ is an effective density. By adding all of these constraints to the CIMDO-objective function (Eq.16), Eq.19 is obtained:

[24] PoD $\cong \frac{CDS}{1-recovery\ rate}$, where recovery rate is approximated to be 40%

$$L[p,q] = \iint p(x,y)\, ln\, p\,(x,y)dxdy - \iint p(x,y)\, ln\, q\,(x,y)dxdy +$$
$$\lambda_1\left[\iint p(x,y)\chi_{[x_d^x,\infty)}dxdy - PoD_t^x\right] + \lambda_2\left[\iint p(x,y)\chi_{[x_d^y,\infty)}\, dydx - PoD_t^y\right] +$$
$$\mu\left[\iint p(x,y)dxdy - 1\right] \qquad (19)$$

where λ_1, λ_2 denote the Lagrange multipliers of the "consistency constraints", and μ the Lagrange multiplier of the "probability additivity constraint". The optimization procedure is performed using the calculus of variations, and its optimal solution is expressed as:

$$p(x,y) = q(x,y)exp\left\{-\left[1 + \mu + \left(\lambda_1\chi_{[x_d^x,\infty)}\right) + \left(\lambda_2\chi_{[x_d^y,\infty)}\right)\right]\right\} \qquad (20)$$

Following this, the PoD of company X conditional on company Y that is in distress could be achieved as below:

$$P(X|Y) = P\left(x \geq x_d^x \middle| y \geq x_d^y\right) = \frac{P(x \geq x_d^x, y \geq x_d^y)}{P(y \geq x_d^y)} \qquad (21)$$

where $P(x \geq x_d^x, y \geq x_d^y)$ is the probability that both X and Y are in distress, and it is obtained by taking the integral of Eq.20 $P(y \geq x_d^y)$ indicates the probability of default of company Y, and it is $\mathrm{PoD}_\mathrm{t}^\mathrm{y}$.

Table 4 presents the DiDe of a system consists of companies X, Y and Z. A pairwise conditional PoD in the matrix refers to the PoD of the company listed in the row, given that the company listed in the column is in default.

Table 4 Distress Dependence Matrix

	X	Y	Z
X	1	P(X|Y)	P(X|Z)
Y	P(Y|X)	1	P(Y|Z)
Z	P(Z|X))	P(Z|Y)	1

Source: Segoviano and Goodhart (2009)

SRISK

SRISK is developed by Acharya et al. (2012) and Brownlees and Engle (2016). It estimates the expected capital shortfall of a financial institution conditional on a substantial market decline. The firm with the greatest capital shortfall is believed to contribute the most to systemic risk and crisis in the financial market. Following Acharya et al. (2012), this thesis defines SRISK as:

$$SRISK_{it} = max[0; k(D_{it} + (1 - LRMES_{it})W_{it}) - (1 - LRMES_{it})W_{it}] \quad (22)$$

where k denotes the prudential capital ratio (following Brownlees and Engle (2016), k = 8% in this thesis), D_{it} the book value of debt, W_{it} the market value of equity. Denote L_{it} the leverage of the firm *i,* with $L_{it} = (D_{it} + W_{it})/W_{it}$, SRISK is the linear combination of a firm's size, leverage and its interconnections with the rest of the system through LRMES:

$$SRISK_{it} = max[0;\ [kL_{it} - 1 + (1-k)LRMES_{it}]W_{it}] \quad (23)$$

$LRMES_{it}$ in Eq.22 and Eq 23 is the long run marginal expected shortfall that measures the expected equity return of a financial institution conditional on the systemic event, and it isexpressed as:

$$LRMES_{it} = -E_t(R_{it+1:t+h}|R_{mt+1:t+h} < C) \quad (24)$$

where $R_{it+1:t+h}$ ($R_{mt+1:t+h}$) is the multi-period arithmetic equity return of firm i (market) between period *t+1*and $t+h$. This thesis follows Brownlees and Engle (2012) and Brownlees and Engle (2016) to estimate LRMES predictions by Monte-Carlo simulations. The estimation is to simulate a random sample of the h-period (following Brownlees and Engle (2016), h = 6 months in this thesis) company and market returns conditional on information available at time t. The LRMES at time t is the average of the Monte-Carlo simulations of h-period company returns when market return is lower than C:

$$LRMES_{it} = -\frac{\sum_{s=1}^{S} R_{it+1:t+h}^{s} I\{R_{mt+1:t+h}^{s} < C\}}{\sum_{s=1}^{S} I\{R_{mt+1:t+h}^{s} < C\}} \quad (25)$$

Follows Brownlees and Engle (2016), C = 40% in this thesis. S, the number of simulations is 10,000. I is the indicator function. In order to be consistent with results of other risk measure, LRMES is obtained for each quarter in the sample, and is then substituted into Eq.23 to obtain quarterly SRISK.

After the initial estimations are made from each of the systemic risk measure, this chapter also makes following processing for results analysis:

(1) Sector Connectedness Analysis

Pairwise analyses in this thesis include risk measures of $\Delta CoRisk$, $\Delta CoVaR$, CDS-based and equity-based Granger-causality tests, CDS-based and equity-based IRF, and DiDe. The result for one quarter from each of the pairwise systemic risk measure is displayed in a 96×96 matrix[25]. Sample periods are from 2005 Q1 to 2014 Q4 (annual for Granger causality and IRF from 2005 to 2014[26]), thus there are 40 matrices (each matrix is 96×96) in total resulted from each risk methodology (10 matrices resulted from Granger-causality test and IRF). LRMES

[25] 96 is the sample size of the institutions included in this research. Pairwise methodologies measure the risk dependence between companies as each of them regressing on or conditional on each of the 96 firms, which generates outcomes of 96×96 matrices.

[26] Since the CDS variations for some firms are limited in the early quarters of the sample, annual regressions are implemented for Granger causality tests and IRF analyses.

and SRISK are not pairwise analysis, and they are formatted in 40×96 matrices (40 quarters and 96 companies) as shown in Eq.28.

$$Matrix_{96,96} =$$

$$\begin{bmatrix} Company_1 - Company_1 & \cdots & Company_1 - Company_{96} \\ \vdots & Company_i - Company_j & \vdots \\ Company_{96} - Company_1 & \cdots & Company_{96} - Company_{96} \end{bmatrix} \quad (26)$$

$$Company_i - Company_j = \begin{cases} B - B, i \in [1,32] \ \ j \in [1,32] \\ B - I, i \in [1,32] \ \ j \in [33,64] \\ B - N, i \in [1,32] \ \ j \in [65,96] \\ I - B, i \in [33,64] \ \ j \in [1,32] \\ I - I, i \in [33,64] \ \ j \in [33,64] \\ I - N, i \in [33,64] \ \ j \in [65,96] \\ N - B, i \in [65,96] \ \ j \in [1,32] \\ N - I, i \in [65,96] \ \ j \in [33,64] \\ N - N, i \in [65,96] \ \ j \in [65,96] \end{cases} \quad (27)$$

The sector connectedness analysis is focusing on 9 pairwise sectors as shown in Eq.27. B, I and N denote banks, insurers and NFIs respectively. Values of the pairwise sectors are computed by averaging the values of pairwise institutions. One exception is that in Granger-causality tests, the sum number of the significant Granger-causal relationships of pairwise firms denotes the connection magnitude between pairwise sectors. In the matrix as shown in Eq. 26, $Company_j$ is the risk contributor to $Company_i$, while $Company_i$ is the risk receiver. That is to say, the column mean of a company represents the systemic importance of this company, while the row mean of a firm signifies the firm's systemic vulnerability. Accordingly, a sector pair such as B-I means that insurers contribute risk to banks, and banks are affected by the insurance sector.

(2) Systemic Importance and Systemic Vulnerability

As mentioned above, column mean value and row mean value of one quarter's result (96x96 matrix) from a pairwise systemic risk methodology are computed to reflect systemic importance and systemic vulnerability of the 96 companies respectively. Systemic importance of a company represents how much risk this company contributes to others, while systemic vulnerability of a company indicates to what extent this company is affected by others. The outputs from these mean calculations for one systemic risk measure are two vectors: one vector with size of 96 represents the companies' systemic importance (column mean) for one quarter, and the other vector with size of 96 indicates companies' systemic vulnerability (row mean) for one quarter. This is repeated for all 40 quarters[27] of one systemic risk methodology, which resulted in a 40×96 matrix as shown in Eq.28. The same is applied to all pairwise systemic risk measures. IRF produces maximum value as well as lasting period in each impulse response plot, thus column mean values and row mean values are computed for both maximum value matrices and lasting period matrices. Since LRMES and SRISK are not pairwise-based risk indicators, their results are directly in 40×96 matrices.

$$\begin{bmatrix} Company_{1,Q1} & \cdots & Company_{96,Q1} \\ \vdots & \ddots & \vdots \\ Company_{1,Q40} & \cdots & Company_{96,Q40} \end{bmatrix} \tag{28}$$

Given the classification of systemic importance and systemic vulnerability, and considering the aim of this thesis to compare the effects of data type on systemic risk evaluations, systemic risk results in the following sections include:

(1) $\Delta CoRisk$ systemic importance

(2) $\Delta CoVaR$ systemic importance

(3) CDS-based Granger-causality test systemic importance

(4) Equity-based Granger-causality test systemic importance

(5) CDS-based IRF maximum values systemic importance

(6) Equity-based IRF maximum values systemic importance

(7) CDS-based IRF lasting periods systemic importance

(8) Equity-based IRF lasting periods systemic importance

(9) DiDe systemic importance

(10) $\Delta CoRisk$ systemic vulnerability

(11) $\Delta CoVaR$ systemic vulnerability

(12) CDS-based Granger-causality test systemic vulnerability

(13) Equity-based Granger-causality test systemic vulnerability

(14) CDS-based IRF maximum values systemic vulnerability

(15) Equity-based IRF maximum values systemic vulnerability

(16) CDS-based IRF lasting periods systemic vulnerability

(17) Equity-based IRF lasting periods systemic vulnerability

(18) DiDe systemic vulnerability

(19) LRMES

[27] 10 years for Granger-causality tests and IRF, which resulted in 10×96 matrices

(20) SRISK

(3) Sector Risk Ranking

Sector risk ranking will be resulted from statistical tests that make pairwise comparisons and risk rankings between sectors. This thesis employs the Conover-Iman test to estimate statistical dominance among multiple pairwise sector pairs (Eq.38) and among pairwise sectors (banks, insurers, NFIs). The Conover-Iman test is chosen because it is a non-parametric test without assuming normal distributions of the sample data. It is also a suitable test to make comparisons among multiple samples rather than comparing only two samples as what the Wilcoxon rank-sum test does.

As mentioned earlier, current literature has provided diversified findings on the systemic relevance of insurance companies relative to banks and other sectors. Some of them compare systemic risk levels of multiple sectors by focusing on connectedness between them, and some others emphasise the region effects on sector risk rankings. This section explores the role of data sources in risk evaluations and attempts to test the first hypothesis as below.

H4.1: Insurers are more systemic relevant than banks and NFIs estimated by systemic risk metrics that are based on some certain types of data, while they are less systemic relevant than the other two sectors measured by risk indicators that are using other data.

Rodríguez-Moreno and Peña (2013) conclude that CDS-based systemic risk measures outperform the methodologies based on equity prices and interbank interest rates. Following them, this section employs manifold leading systemic risk methodologies to compare the performance of CDS-based, equity-based, and balance sheet-based risk assessments in providing early risk warnings, and attempts to test the second hypothesis as below.

H4.2: CDS-based systemic risk methods provide earlier risk warning signals than non-CDS-based systemic risk methods.

4.1.2 Data

Data employed in this thesis has been described in Chapter 3. Table 5 displays data requirements of the systemic risk methodologies employed in this chapter. The descriptive statistics of CDS spread, equity returns are listed in Chapter 3. This section demonstrates the descriptive statistics of leverage and market capitalisation.

Table 5 Data Requirements of Systemic Risk Measures

	Data	Data type	Frequency	Sample
$\Delta CoRisk$	CDS spread	Market	Daily	3/1/2005–31/12/2014
$\Delta CoVaR$	Equity return	Market	Daily	3/1/2005–31/12/2014
Granger causality	CDS vs. equity	Market	Daily	3/1/2005–31/12/2014
IRF	CDS vs. equity	Market	Daily	3/1/2005–31/12/2014
DiDe	CDS spread	Market	Daily	3/1/2005–31/12/2014
SRISK	Equity return, market return, leverage, market capitalisation	Market, accounting	Daily, quarterly	3/1/2005–31/12/2014, 2005 Q1–2014 Q4

Source: Datastream

Table 6 and Table 7 show the descriptive statistics of leverage and market capitalisation respectively. In Table 6, banks are associated with higher leverage than insurers in terms of mean and data variation, however the insurance sector has a higher maximum figure than that of the banking sector. As can be seen from Table 7, non-financial institutions are the largest in terms of market capitalisation, followed by banks, and insurers are with the smallest size as shown in Table 20.

Table 6 Descriptive Statistics of Leverage

Sector	Mean	St.Dev.	Min	Max
Banks	24.18309	24.28854	1.035461	248.682
Insurers	13.14588	18.92014	1.30439	288.2429
NFIs	1.610835	0.5950386	1.068364	7.184115
Total	12.97993	20.02187	1.035461	288.2429

The table presents mean values, standard deviations, minimum values and maximum values of leverage for each of the 3 sectors. Sample period ranges from 2005 Q1 to 2014 Q4, thus there are 40 observations for each company and 1280 (32×40) observations for each sector.

Table 7 Descriptive Statistics of Market Capitalisation

Sector	Mean	St.Dev.	Min	Max
Banks	64041.63	51511.89	4675.244	276774.6
Insurers	24641.03	28859.99	87.67	186295.9
NFIs	115294	76494.52	18137.51	513307.4
Total	67992.24	66998.49	87.67	513307.4

The table presents mean values, standard deviations, minimum values and maximum values of market capitalisation for each of the 3 sectors. Sample period ranges from 2005 Q1 to 2014 Q4, thus there are 40 observations for each company and 1280 (32×40) observations for each sector.

4.2 Sector Connectedness Analysis

4.2.1 Results of Sector Connectedness Analysis

$\underline{\Delta CoRisk\ vs.\ \Delta CoVaR}$

For the pair of $Industry_m$ - $Industry_n$ ($m \in [Banks, Insurers, NFIs], n \in [Banks, Insurers, NFIs]$), $\Delta CoRisk$ measures the difference between the credit risk of $Industry_m$ conditional on $Industy_n$ in an extreme event and the credit risk of $Industry_m$

conditional on $Industry_n$ in a median state. Taking the pair of B-I as an example, it experiences its highest $\Delta CoRisk$ value of 0.0856 in 2007 Q3. It means that on average the credit risk of banks, if affected by insurers that are in a distressed time, is 8.56% higher than if the insurers are in a tranquil time. Similarly, $\Delta CoVaR$ is the difference between the VaR of $Industry_m$ conditional on $Industry_n$ in an extreme event and the VaR of $Industry_m$ conditional on $Industry_n$ in a normal state. Taking the pair of I-B as an example, it peaks in 2008 Q4 with a value of 0.0472. It means that on average the risk of insurers if influenced by banks that are in a tail event, is 4.72% higher than if banks are in their normal states. The higher the $\Delta CoRisk/\Delta CoVaR$, the higher the risk dependence is between sectors.

Error! Reference source not found. compares the trends of the 9 pairs indicated by $\Delta CoRisk$ and $\Delta CoVaR$. For $\Delta CoRisk$, B-B dominates most of the sample period. This suggests that links between banks were the strongest compared with other pairs. Since 2007 Q3, I-B is the second highest in each of the spikes excluding in 2008 Q4 where I-I (0.0844) is greater than I-B (0.0738). High values of both I-B and I-I indicate that both banks and insurers substantially contributed risk to insurers since the crisis started. Except I-N, N-N, and I-I, which peak in 2008 Q4, all other pairs peak in 2007 Q3. Each group of i-B, i-I and i-N (i=B, I, N) has the same trend respectively, meaning that each industry affected all the three sampled industries in a particular and identical pattern from 2005 Q1 to 2014 Q4. In terms of $\Delta CoVaR$, all 9 pairs have shown little difference in their patterns, with the same peaks in 2008 Q4 (all pairs except B-B and B-I) or in 2009 Q1 (B-B, B-I). In 2008 Q4, I-I (0.0519) is at the top, followed by B-B (0.0499), and I-N (0.0498), while in 2009 Q1, B-B (0.0517) dominates others, with B-I (0.0467) and I-I (0.0461) being the second and the third respectively. That is to say, linkages within insurance, within banking, and between insurance and banking were relatively higher during the financial crash.

Both $\Delta CoRisk$ and $\Delta CoVaR$ have recognised historical shocks by showing spikes in the corresponding quarters: The collapses of BNP Paribas Hedge Funds and Bear Stearns Hedge Funds in 2007 Q3, Greek bailout in 2010 Q2, and US debt ceiling crisis in 2011 Q3 and 2013 Q2. The differences between $\Delta CoRisk$ and $\Delta CoVaR$ are that pairs indicated by $\Delta CoRisk$ peak in 2007 Q3 or 2008 Q4 with some of them experiencing the second greatest values in 2008 Q3 when Lehman Brothers announced bankruptcy and AIG acquired bailout, whereas pairs suggested by $\Delta CoVaR$ peak in 2008 Q4 or 2009 Q1. This would suggest that $\Delta CoRisk$ (CDS-based) is superior to $\Delta CoVaR$ (equity-based) in terms of providing slightly earlier risk warning signal. In addition, values of the 9 pairs presented by $\Delta CoRisk$ are more dispersed than those presented by $\Delta CoVaR$. Generally, both agree that three green lines (N-B, N-I, and N-N), representing systemic vulnerability of NFIs, are relatively at the lowest levels in the majority of the time.

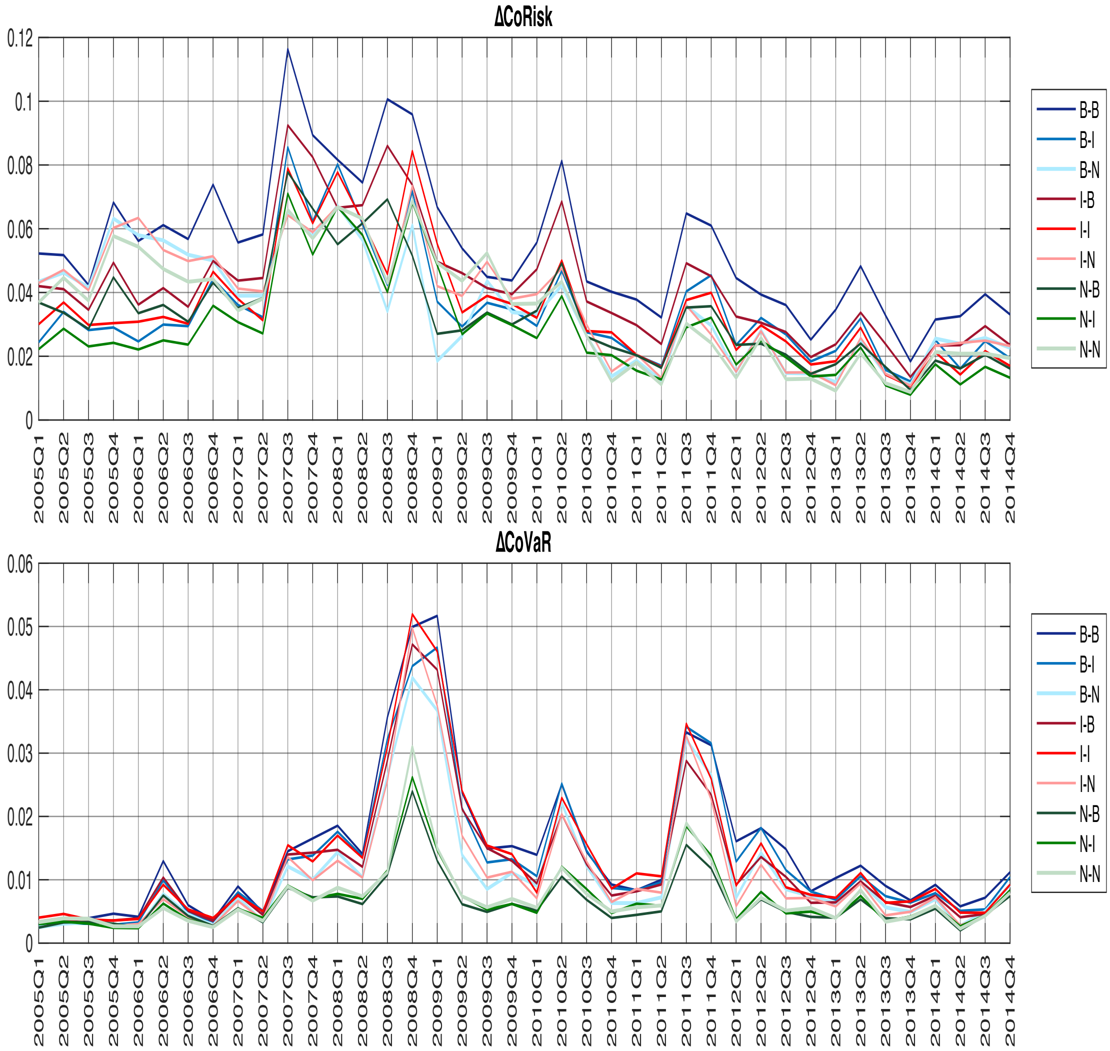

Figure 8 Industry Connectedness Estimated by $\Delta CoRisk$ and $\Delta CoVaR$

The figure compares the industry connectedness measured by ΔCoRisk with that estimated by ΔCoVaR. The values of the 9 pairwise sectors are computed by averaging the values of pairwise institutions. B, I, N represent banks, insurers and NFIs respectively. The sector on the left is the risk receiver, while the sector on the right is the risk contributor.

Error! Reference source not found. compares the variations of the 9 pairs in terms their standard deviations evaluated by $\Delta CoRisk$ and $\Delta CoVaR$. Sub-plots in **Error! Reference source not found.** have shown roughly similar trends to those in **Error! Reference source not found.**. With respect to $\Delta CoRisk$, three pairs in each column of the figure, i.e. the systemic importance of each industry, have presented the same patterns of fluctuations. However, the patterns are distinct between columns. Specifically, the first column with banks being risk contributors (B-B, I-B, N-B), and the third column with NFIs being the risk triggers (B-N, I-

N, N-N) have shown high volatility before 2007 Q3, which is not the case in the second column (B-I, I-I, N-I). The data variations shown in the column 3 of the figure are higher before 2006 Q1 than in the crisis periods. This might be due to the liquidity problem of the CDS data in the early quarters especially for NFIs. Regarding $\Delta CoVaR$, values of all 9 pairs behave similarly. The 3rd row, which denotes the systemic vulnerability of NFIs, has shown the smallest data dispersion, which once again confirms that compared with banks and insurers, NFIs are more stable throughout the sample period.

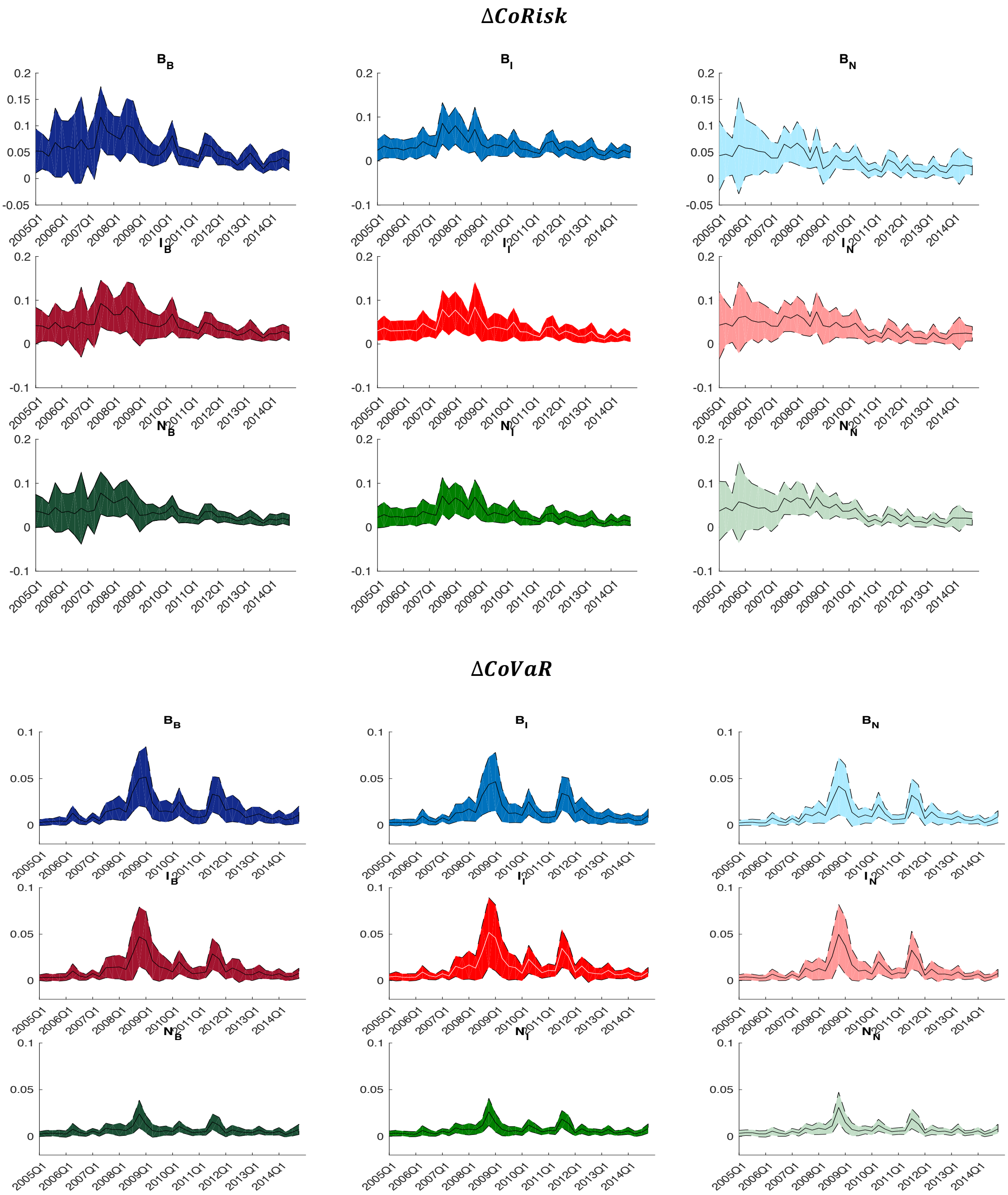

Figure 9 Variations in the Industry Connectedness Estimated by $\Delta CoRisk$ and $\Delta CoVaR$

The figure compares the standard deviations of the industry risk dependences measured by $\Delta CoRisk$ with those estimated by $\Delta CoVaR$. The dispersions of the 9 pairwise sectors in the figure are obtained by computing the standard deviations of the pairwise sector values in **Error! Reference source not found.**. B, I, N represent banks, insurers and NFIs respectively. The sector on the left is the risk receiver, while the sector on the right is the risk contributor.

CDS-based Granger-Causality tests vs. Equity-based Granger-Causality tests

Error! Reference source not found. compares the sector connectedness computed from

Granger causality using CDS data with that using equity data. The total number of the significant Granger-causal relationships among institutions represents the value of a corresponding pair of sectors. The greater the significant numbers, the stronger connections are between the industries. The first row in **Error! Reference source not found.** compares the significant connection numbers in each pair of sectors measured by CDS-based Granger-causality tests with that estimated by equity-based Granger-causality tests. With regard to the results based on CDS spread, pairs peak in different years and there are greater gaps between each pairs since 2007, the beginning of the subprime mortgage crisis. From 2005 to 2007, I-I is at the top, followed by B-B, I-B and B-I with B-I being the second riskiest in 2007, which emphasises the systemic importance of insurers and the linkages between banks and insurance companies. After 2007, all pairs maintain higher values until 2012. As for the results based on equity data, pairs climb into their maximum values in 2008, instead of in 2007 that is shown in the CDS-based chart, which might signify the earlier risk-indicating feature of CDS data. After 2008, sector connections start to stabilise. Generally, I-B, B-B and N-B occupy the higher positions, with I-I, B-I and N-I roughly coming as the second high groups, and B-N, I-N and N-N the lowest group. This is to say, banks significantly Granger caused the highest quantity of the companies in the sample, and insurers significantly Granger caused the second most companies. The second row in **Error! Reference source not found.** provides the accumulated significant Granger-casual relationships of each pair of sectors resulted from CDS-based and equity-based assessments. By contrast, the stacked values obtained from CDS data are greater and remain at high levels longer than those estimated from equity data for most of the sample periods. This implies that credit risk links between industries are stronger than other risk forms of connections.

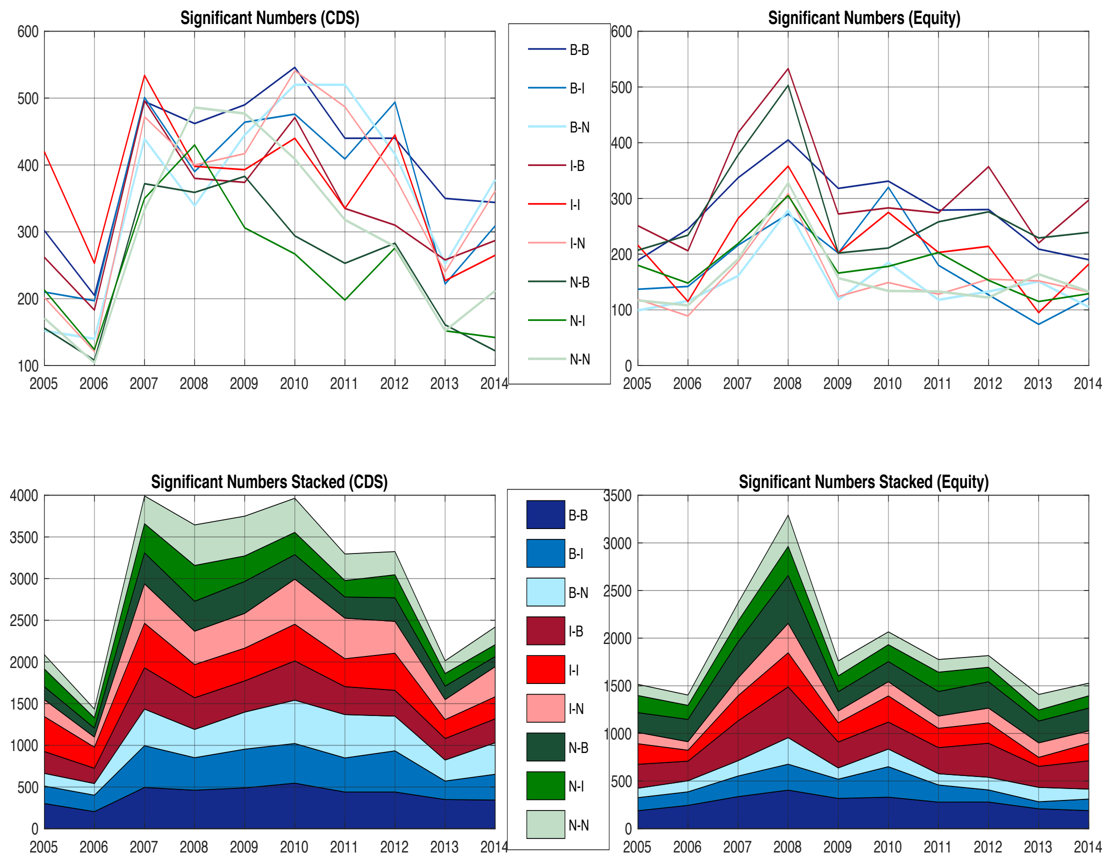

Figure 10 Industry Connectedness Estimated by CDS-Based Granger-Causality Tests and Equity-Based Granger-Causality Tests

The figure compares the industry risk dependences measured by CDS-based Granger-causality tests with those estimated by equity-based Granger-causality tests. Sums of the significant Granger-causal relationships of the pairwise firms denote the magnitudes of the corresponding pairwise sectors. B, I, N represent banks, insurers and NFIs respectively. The sector on the left is the risk receiver, while the sector on the right is the risk contributor.

CDS-based IRF vs. Equity-based IRF

For the pair of $Industry_m$ - $Industry_n$ ($m \in [Banks, Insurers, NFIs], n \in [Banks, Insurers, NFIs]$), impulse response function (IRF) measures when there is a one standard deviation shock to $Industry_n$, what are the maximum value and duration of the response from $Industry_m$ to the impulse. The maximum value and duration for a pair of sectors are the averages of the maximum values and lasting periods for pairwise institutions. Higher peak values and longer lasting periods indicate deeper risk transfers. For example in **Error! Reference source not found.**, B-I resulted from the CDS-based IRF (equity-based IRF) has on average a maximum value of 0.5706 (0.4042) and a lasting period of 6.2410 (5.9007) in 2008. This means that a one standard deviation shock to the insurance sector, on average, causes a maximum increase of 0.5706 (0.4042) in banks, and this effect will sustain until after about 6.2410 (5.9007) periods.

Error! Reference source not found. compares the impulse response analyses built on CDS spread and equity returns. The upper two sub-plots illustrate the maximum values of the pairwise sectors measured by CDS-based IRF and equity-based IRF respectively. In terms of the average maximum values based on CDS, all pairs peak in 2008 excluding I-B that reaches its top in 2010. In 2008, B-I, I-I and B-B are the highest three groups, signifying the systemic importance of insurance industry. Following 2008, pairs remain unstable with their maximum values of responses to shocks keeping at high levels. Since 2010, B-B, B-I, I-I and I-B dominate over other pairs, highlighting the connections between and within banks and insurers. Regarding the equity-based mean maximum values, pairs of sectors have captured the distress in 2008 and the US debt ceiling crisis in 2011 by showing spikes in these two years. B-B, B-I, and I-I lead other pairs for most of the years, which underlies the risk contributions of insurance companies and the links between the banking and insurance sectors.

The lower two sub-plots in **Error! Reference source not found.** demonstrate the lasting periods of the pairwise sectors indicated by CDS-based IRF and equity-based IRF respectively. With regard to the CDS-based lasting periods, they sustain longer in 2005 and 2006 when the CDS-based maximum values in the top left sub-plot are at the bottom levels. This may be because that CDS spread is less liquid in 2005 and 2006. In 2007, when the financial meltdown is breeding, the lasting periods of I-I, I-B, B-B and B-I are longer than other pairs, which is consistent with the conclusion of the CDS-based maximum values that emphasises the connection between banks and insurers. The lasting periods stabilise after 2007. As for the equity-based lasting periods in the bottom right sub-plot, pairs reach relatively higher levels in 2008 and 2011, which is consistent to what is shown in the sub-plot of the equity-based maximum values. However, all pairs are less fluctuant and no valuable information is provided.

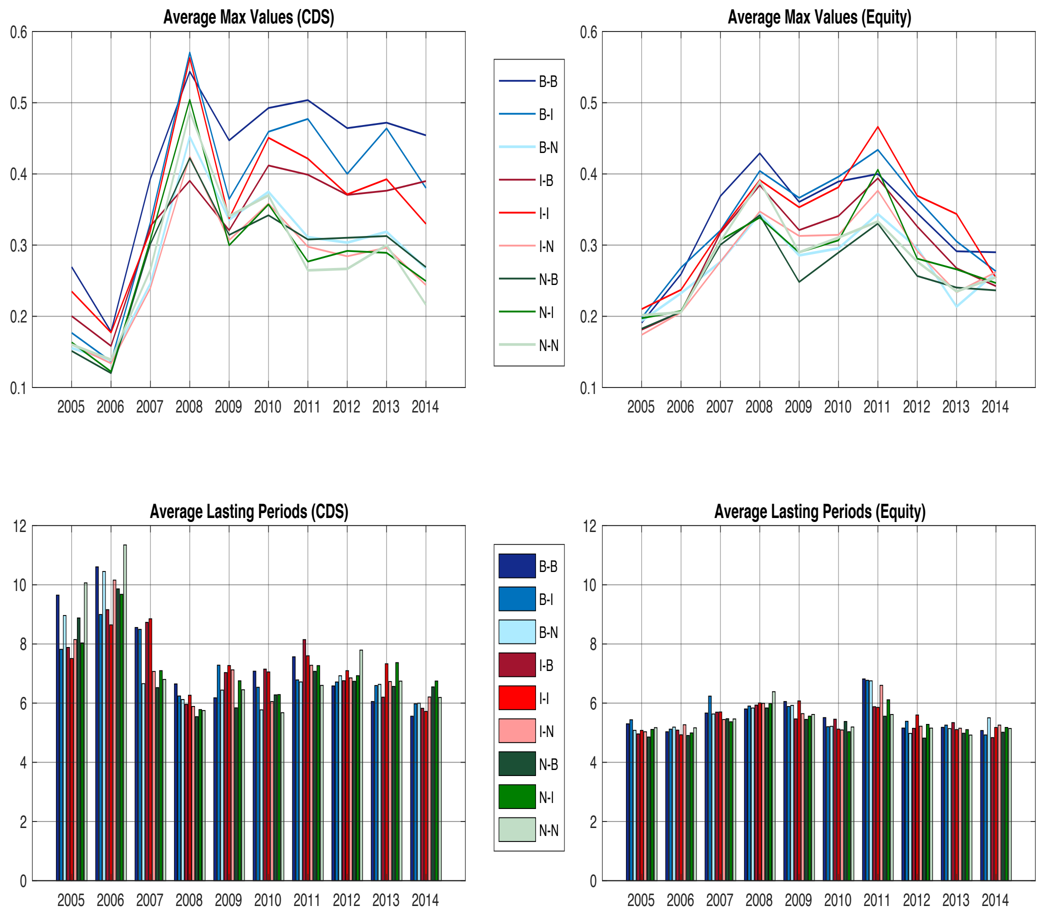

Figure 11 Industry Connectedness Estimated by CDS-Based IFR and Equity-Based IFR

The figure compares the industry risk dependences measured by CDS-based IRF with those estimated by equity-based IRF. IRF produces the maximum value and lasting period of the response of an industry to the impulse of a one standard deviation shock. The maximum values and lasting periods for the 9 pairwise sectors are analysed separately. B, I, N represent banks, insurers and NFIs respectively. The sector on the left is the risk receiver, while the sector on the right is the risk contributor.

<u>*DiDe*</u>

Error! Reference source not found. exhibits the industry connectedness evaluated by Distress Dependence Matrix (DiDe). For the pair of $Industry_m$ - $Industry_n$ ($m \in [banks, insurers, NFIs]$, $n \in Banks, Insurers, NFIs]$), DiDe denotes the probability of default (PoD) of $Industry_m$ conditional on $Industry_n$ that is in distress. The higher the figure, the higher the credit risk linkages are. For example, I-B peaks in 2009 Q1 with a value of 0.2771, and it means that the PoD of insurers conditional on banks that are in extreme event is on average of 0.2771.

In **Error! Reference source not found.**, the system of red lines peak in 2009 Q1, the system of green lines achieve tops in 2008 Q4, and the system of blue lines reach their maximums in 2011 Q4 with spikes in 2008 Q3 and 2009 Q1. The three colour systems in **Error! Reference source not found.** have also shown distinctive levels based on their colours: three lines in the red system dominate the majority of time; three lines in the blue system roughly come in the middle; three lines in the green system are mainly at the bottom. This ranks the systemic risk vulnerability of the industries as insurers > banks > NFIs. Within the three red lines, I-I leads most of the time since 2007 Q3, whereas within the three blue lines, B-B dominates the whole periods.

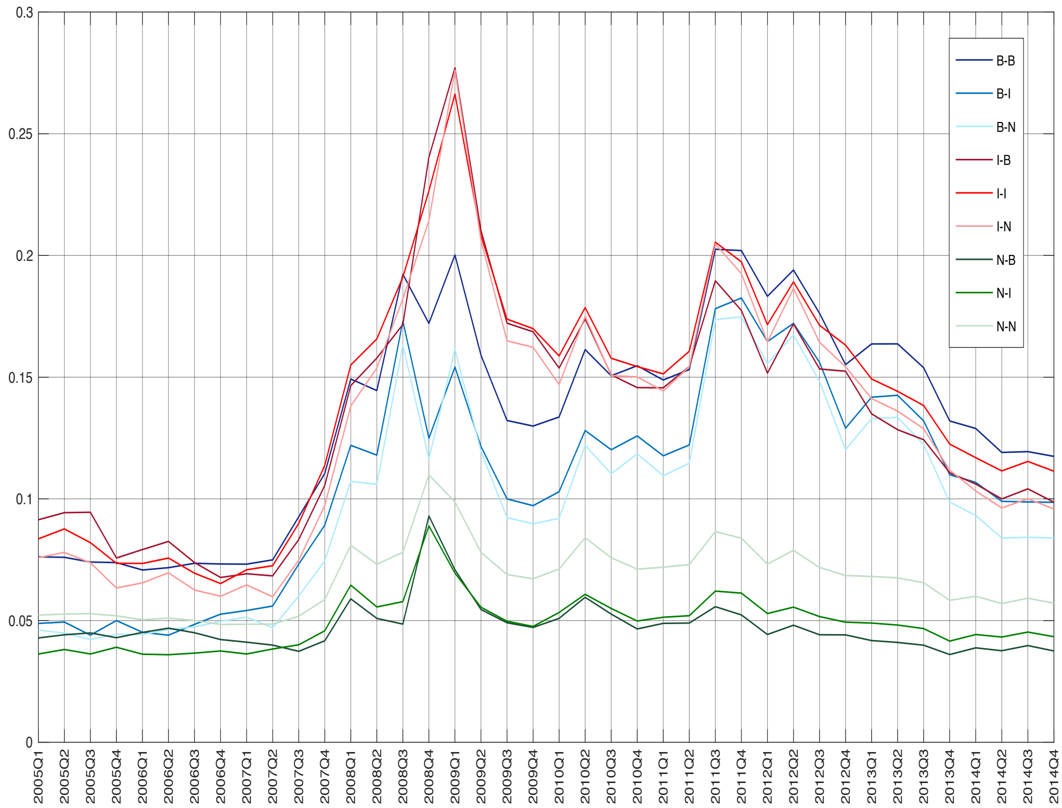

Figure 12 Industry Connectedness Estimated by DiDe

The figure demonstrates the industry connectedness measured by DiDe. The values of the 9 pairwise sectors are computed by averaging the values of pairwise institutions. B, I, N represent banks, insurers and NFIs respectively. The sector on the left is the risk receiver, while the sector on the right is the risk contributor.

Error! Reference source not found. discloses the variation, i.e. standard deviation, of the conditional PoD for each sector connections. The variations of the band areas are consistent with the patterns presented by the mean values in **Error! Reference source not found.**. The red areas in the second row have wider bands than the blue areas in the first row and the green areas in the last row. This reaffirms that insurance were the most susceptible industry, with banking as the second fragile sector.

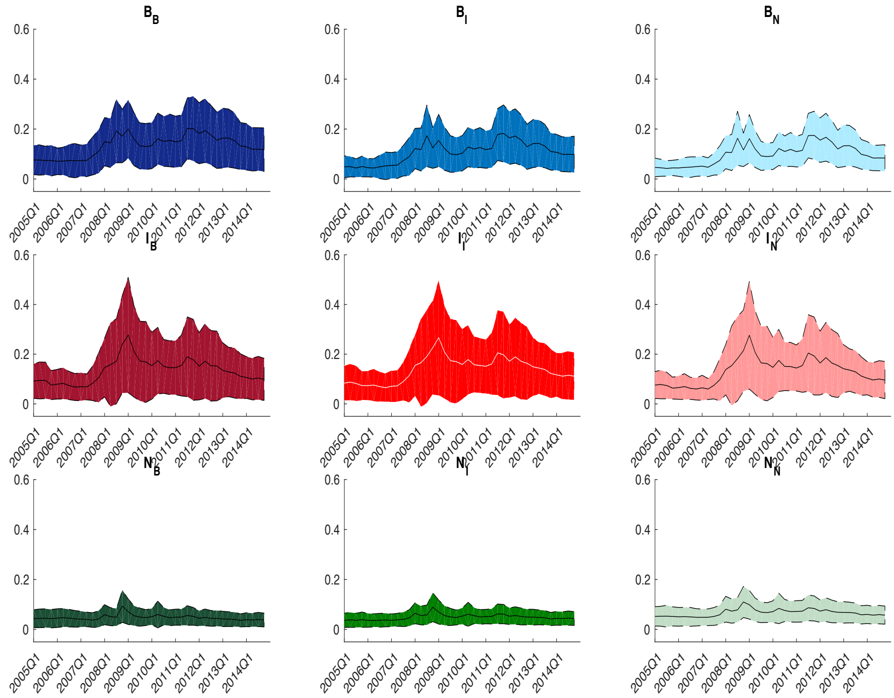

Figure 13 Variations in the Industry Connectedness Estimated by DiDe

The figure compares the standard deviations of the industry risk dependences measured by DiDe. The dispersions of the 9 pair of sectors in the figure are obtained by computing the standard deviations of the pairwise sector values in **Error! Reference source not found.**. B, I, N represent banks, insurers and NFIs respectively. The sector on the left is the risk receiver, while the sector on the right is the risk contributor.

4.2.2 One-Sample Wilcoxon Signed-Rank Test

Before implementing the Conover-Iman test as the dominance test on systemic risk results to compare pairwise sector connectedness, this section first performs the one-sample Wilcoxon signed-rank test as the significance test.

Similar to Chapter 3, the one-sample Wilcoxon signed-rank test is implemented in this section to investigate whether the systemic risk results are significantly different from zero. The reason to select the one-sample Wilcoxon signed-rank test is explained in Chapter 3. The one-sample Wilcoxon signed-rank test is carried out on each of the time series of the 96 companies for each of the systemic risk measure. The null hypothesis is that the data follow a distribution whose median is zero. Appendix 31 has shown the one-sample Wilcoxon signed-rank test results for systemic risk measures.

4.2.3 Kruskal-Wallis Test

Kruskal-Wallis test is applied to investigate whether the systemic risk measures employed in this thesis are significantly different from each other. Similar to the firm-level risk analysis, this section adopts the Kruskal-Wallis test to examine whether distinct samples come from the same distribution. In addition, Kruskal-Wallis test is to compare two or more independent samples, which is suitable to be applied in this section that includes 20 systemic risk estimations.

After obtained companies' systemic importance and systemic vulnerability from the pairwise systemic risk methodologies, all 20 systemic results are presented in 40×96 matrices (40 quarters and 96 companies). Given that these outcomes are panel data, this section performs the Kruskal-Wallis test on time series: first perform one Kruskal-Wallis test on the 20 systemic risk measures by using the time series data of the first company. This is then repeated for all the other 95 companies. Eventually, there are 96 outputs resulted from Kruskal-Wallis tests on 96 companies. The null hypothesis of the test is that all samples follow the same distribution, while the alternative hypothesis is that not all samples are the same.

Appendix 32 presents the Kruskal-Wallis test results on systemic risk measures. Appendix 33 displays the results of Kruskal-Wallis tests on both firm-level risk measures and systemic risk measures. All these three appendices indicate that at least one risk methodology in the comparison sample is significantly different from at least one other risk indicator.

4.2.4 Conover-Iman Test on the Results of Sector Connectedness Analysis

As mentioned in Chapter 3, the Kruskal-Wallis test is not able to recognise which specific sample dominates which another, so a post hoc test is required. The Conover-Iman test, which evaluates statistical dominance among multiple pairwise comparisons after a Kruskal-Wallis test, is adopted in this section as the post hoc test. The reason for this choice is explained in Chapter 3.

This section has compared the connectedness strength of pairwise sectors. It is achieved by implementing Conover-Iman tests to compare the time series of the 9 sector pairs: B-B, B-I, B-N, I-B, I-I, I-N, N-B, N-I, N-N, each of which has 40 quarterly data[28]. The values for these pairs are obtained from Eq.27.The connectedness strength rankings are performed for each of the three time periods – the pre-crisis period (2005 Q1 to 2007 Q2, 10 quarterly data), the crisis period (2007 Q3 to 2009 Q2, 8 quarterly data) and the post-crisis period (2009 Q3 to 2014 Q4, 22 quarterly data) to identify ranking changes across crisis phases.[29] The null hypothesis for each pairwise comparison is that there is equal possibility that a randomly selected risk level from one sector pair is greater than the random selected risk level from the other sector pair. The alternative hypothesis is that one sector pair's risk statistically dominates the other one.

Appendices from Appendix 34 to Appendix 38 have shown the results of the Kruskal-Wallis rank sum test and the Conover-Iman test on pairwise sector connections by time for

[28] 10 annual data for pairs resulted from Granger-causality test and IRF

[29] The Conover-Iman test is applied to the whole sample (10 years) for Granger-causality tests and IRF. This is because there are 9 variables to compare, but the subsample of pre-crisis, crisis and post-crisis period include less data than the number of variables.

$\Delta CoRisk$, $\Delta CoVaR$, CDS-based Granger-causality test, equity-based Granger-causality test, CDS-based IRF maximum values, equity-based IRF maximum values, CDS-based IRF lasting periods, equity-based IRF lasting periods and DiDe respectively. Given that results of IRF are at annual frequency, Conover-Iman tests on Granger-causality tests and IRF are implemented on the whole sample period (10 years in total) rather than on the each of the three crisis phases. The statistically significant rankings of pairwise sector connectedness in each appendix are generally consistent with what can be observed from the corresponding line plots[30]: Appendix and 34 Appendix 35 support the plot patterns in Figure 8($\Delta CoRisk$ vs. $\Delta CoVaR$); Appendix 36 confirms the line patterns in Figure 10(CDS-based Granger-causality test vs. equity-based Granger-causality test); Appendix 37 is consistent with Figure 11(CDS-based IRF maximum values vs. equity-based IRF maximum values vs. CDS-based IRF lasting periods vs. equity-based IRF lasting periods); Appendix 38 is in accordance with Figure 12(DiDe).

4.3 Sector Risk Ranking

4.3.1 Sector Risk Comparison Results from SRISK

Sector risk comparisons in this section will be resulted from Conover-Iman tests on systemic risk measures. Without using any statistical tests, Brownlees and Engle (2016) have compared risk levels among different sectors using aggregated SRISK. This section follows Brownlees and Engle (2016) to present results of aggregated SRISK by sector as well in addition to Conover-Iman tests in Section 4.3.2.

According to Brownlees and Engle (2016), sector aggregated SRISK computed by summing the positive SRISK values of the companies within a particular industry is obtained to represent industry risk as well. As can be seen from Figure 14, aggregate SRISK by industry in the two sub-plots have disclosed that banks are associated with the greatest capital shortfalls than insurers and NFIs, with NFIs almost having zero contributions to the SRISK metric. Both banking and insurance sector peak in 2008 Q3 and have other large and small spikes in 2008 Q1 (subprime mortgage crisis), 2010 Q2 (Greek bailout), and 2011 Q3 (US debt ceiling crisis).

[30] Insignificant results may be due to the small sample size. Even if some results are insignificant, the signs of the coefficients are still consistent with what can be observed from the line plots.

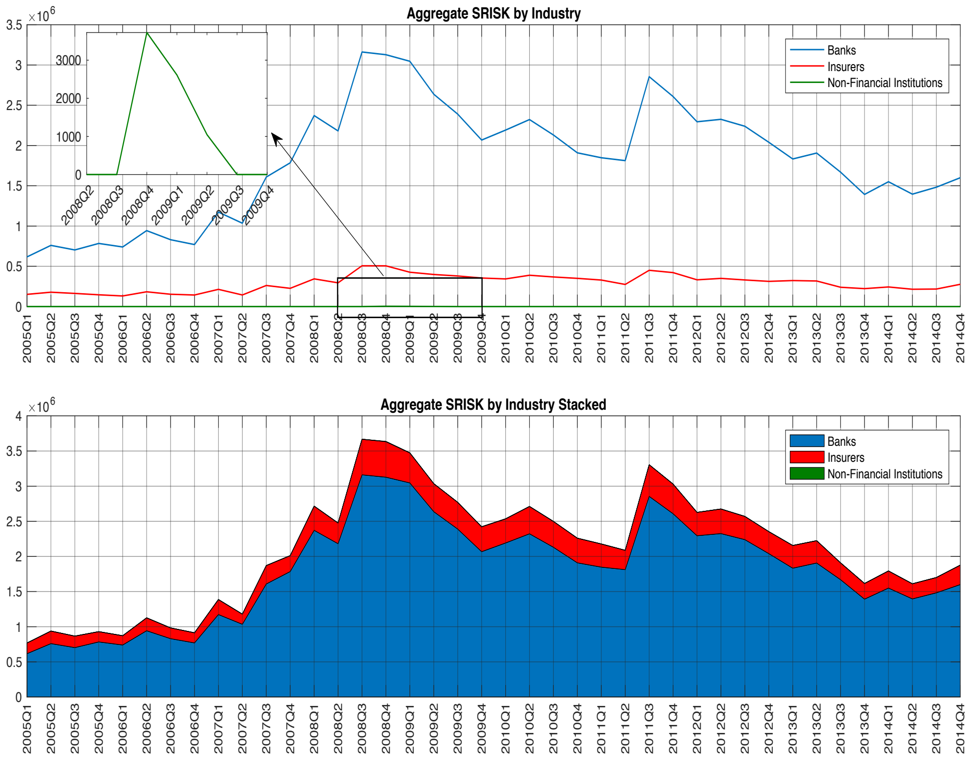

Figure 14 Aggregate SRISK by Industry

Figure 15 has decomposed SRISK by the average values of its input variables, market values, leverage, and LRMES, and compares these inputs with aggregate SRISK by industry. Market values suggest that NFIs in the sample have the largest size, while insurance is the smallest sector. Leverage, however, has disclosed that banks exceed insurers, and both of them have much higher leverage than NFIs. With regard to LRMES, the riskiness of banking and insurance approximately equals with banking being slightly higher in most of the time. Finally, aggregate SRISK reveal that the overall capital shortage of the banking industry is greater than insurers. Four sub-plots together imply that the although sector rankings in terms of aggregate SRISK is different from those of sizes, however the magnitudes of market values contribute to a large extent to the huge gap between the aggregate SRISK of banks and insurers. This is due to that LRMES, excluding the size effect, has roughly equated the riskiness of banks and insurance companies. Leverage has also affected the results of aggregate SRISK, especially affected the rankings of NFIs as the lowest sector although it has the largest size.

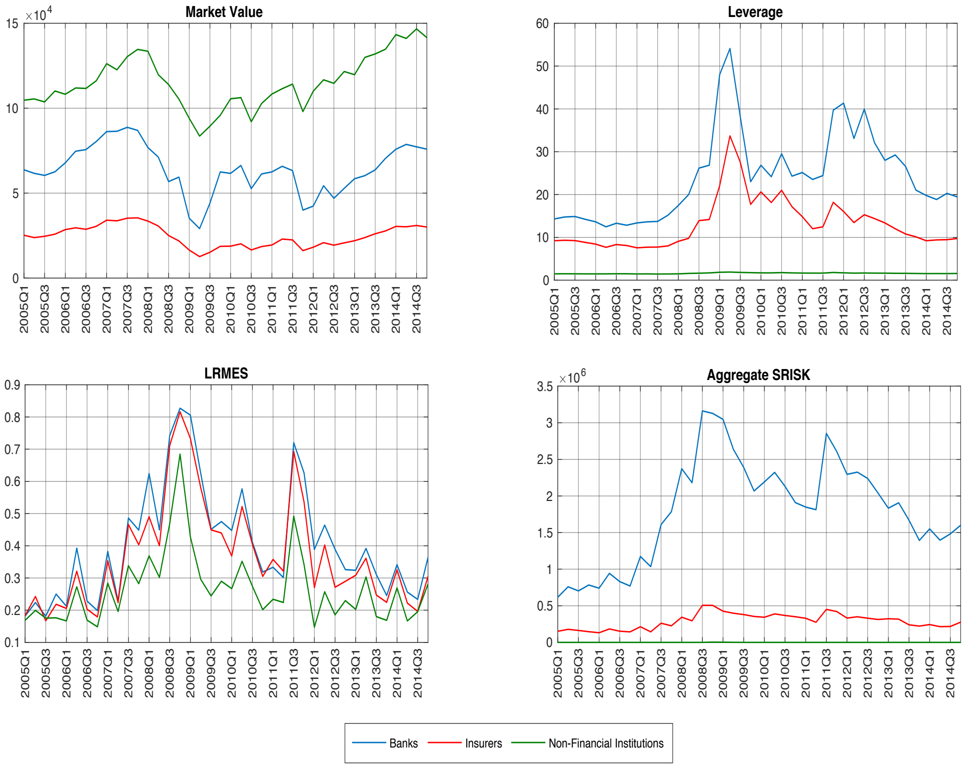

Figure 15 SRISK Decomposition

4.3.2 Conover-Iman Test for Sector Risk Ranking

Sector risk ranking is obtained by running the Conover-Iman test on the systemic risk levels of the three sectors – banks, insurers and NFIs. For each resulted 40×96 matrix (40 quarters and 96 companies) from each systemic risk measure, sector risk levels are obtained by taking average across companies. Following this, all sector risk values are grouped into three time periods – the pre-crisis period (2005 Q1 to 2007 Q2, 8 quarterly data), the crisis period (2007 Q3 to 2009 Q2, 10 quarterly data) and the post-crisis period (2009 Q3 to 2014 Q4, 22 quarterly data). For each of the three-time period, sector risk is ranked by the Conover-Iman test. The null hypothesis for each pairwise comparison is that there is 50 per cent probability that a randomly selected risk level from one sector is higher than the random selected risk level from the other sector. The alternative hypothesis is that one sector's risk statistically dominates the other one.

Appendices from Appendix 39 to Appendix 58 have shown the results of the Kruskal-Wallis rank sum test and the Conover-Iman test on three sectors by time for each systemic risk measure respectively. Take "Insurers - NFIs" as an example, it means the rank difference between insurers and NFIs (i.e. insurers minus NFIs). If t statistic is positive (negative), it indicates that insurers are riskier (less risky) than NFIs. The adjusted P values are in brackets.

According to appendices from Appendix to Appendix, ΔCoRisk Systemic Vulnerability, ΔCoVaR Systemic Vulnerability, CDS-based IRF Maximum Values Systemic Importance, DiDe Systemic Vulnerability, LRMES and SRISK have shown that banks and insurers are significantly riskier than NFIs. This supports what happened during the subprime mortgage crisis. In terms of the risk ranking between banks and insurers, most systemic importance indicators (ΔCoRisk Systemic Importance, Equity-based Granger-causality test Systemic Importance, CDS-based IRF Maximum Values Systemic Importance, DiDe Systemic Importance) suggest that insurers were less riskier than banks, while systemic vulnerability analyses (ΔCoRisk Systemic Vulnerability, ΔCoVaR Systemic Vulnerability, DiDe Systemic Vulnerability) indicate that risk levels of insurers were great than or at least approximately equal to that of banks. This imply that banks were the main risk contributor in the 2007-2009 financial meltdown, while insurers were affected the most during the crisis.

4.3.3 Conover-Iman Test for Comparing Risk between Time Periods

This thesis has also compared systemic risk among three time periods – pre-crisis (2005 Q1 to 2007 Q2), crisis (2007 Q3 to 2009 Q2) and post-crisis period (2009 Q3 to 2014 Q4). Specifically, for each resulted 40×96 matrix (40 quarters and 96 companies) from each systemic risk measure, one company's risk magnitude within each of the three time periods is obtained by taking average across the corresponding quarterly values of this company. Subsequently, these companies' risk values for each time period are grouped by sectors. For each sector, risk levels of three time periods are ranked by the Conover-Iman test. The null hypothesis for each pairwise comparison is that there is an equal chance that a randomly selected risk value from one risk period is higher than the random selected risk value from another time period. The alternative hypothesis is then that the risk of one time period significantly dominate the other one.

Appendices from Appendix 59 to Appendix 78 have shown the outcome of the Kruskal-Wallis rank sum test and the Conover-Iman test that compare systemic risk among the pre-crisis period, crisis period, and post-crisis period by sector. The pair of "Crisis – Pre-crisis" represents the risk rank difference between the crisis period and the pre-crisis period (i.e. crisis minus pre-crisis). A positive (negative) t statistic suggests that risk in the crisis period is higher (lower) than that of the pre-crisis period. Adjusted P values are in brackets is. According to these appendices, Conover-Iman tests on all systemic risk measures except SRISK suggest that crisis period is significantly riskier than the pre-crisis period for all three sectors. These findings support the evidence from the subprime mortgage crisis. As can be seen from Appendix, tests results on SRISK are only significant for banks. This could be explained by Figure, which illustrates that SRISK is comprised of market values, leverage and LRMES. According to Figure, the leverage of NFIs is close to zero, while market values of insurers are relatively small, therefore SRISK values of NFIs and insurers are much smaller than that of banks, resulting in only significant tests outcomes for banks. In addition, most systemic risk measures generally indicate that the crisis period is also significantly risker than the post-crisis period. In terms of the comparison between the pre-crisis period and the post-crisis period, ΔCoRisk Systemic Importance, ΔCoRisk Systemic Vulnerability, CDS-based IRF Lasting Periods Systemic Importance, CDS-based IRF Lasting Periods Systemic Vulnerability show that the pre-crisis period is associated with higher risk than the post-crisis period. All other systemic risk indicators, however, present the opposite ranking for these two periods.

4.4 Rank Correlations across the Systemic Risk Measures and across Time

4.4.1 Rank Correlations across the Systemic Risk Measures

Following Brownlees and Engle (2016), this thesis employs Spearman's ρ, the rank correlation method, to measure the non-linear correlation of the firm-level risk results across risk measures and across time.

Rank correlation across systemic risk measures is carried out on cross-sectional data. Specifically, rank correlation using cross-sectional data is to take average across quarters for each company and correlate the cross-sectional data of each risk indicator with that of each of the other risk methodology.

Appendix 79 presents the results of rank correlations across the systemic risk measures using cross-sectional data. The appendix has shown that most systemic risk indicators in this thesis are significantly positively correlated with others. There are negative spearman's correlations as well. First, all negative numbers are relatively small, with their values greater than -0.44, and most of them are greater than -0.3. Second, negative correlations are basically between risk indicators that are based on different information or are measuring different dimensions of pairwise systemic risk. For example, some negative correlations are between CDS-based and equity-based risk measures, while other negative values are between systemic importance of a risk measure and systemic vulnerability of a risk measure. This implies that CDS and equity data provide slightly different signal in risk estimations. This makes sense as CDS particularly measures credit risk, while equity return represents general risk of a company. It also indicates that the systemic importance of a company is different from the systemic vulnerability of the company.

4.4.2 Rank Correlations across Time

Spearman's rank correlation across time is to correlate systemic risk among distinct time periods: pre-crisis, crisis, and post-crisis period for each of the systemic risk measures. Pre-crisis period includes quarters from 2005 Q1 to 2007 Q2, crisis period from 2007 Q3 to 2009 Q2, and post-crisis period from 2009 Q3 to 2014 Q4.

Appendix 80 demonstrates the resulted rank correlations across time for systemic risk measures. As can be seen from the Appendix, crisis period is significantly correlated with the post-crisis period at a relatively stronger level for all systemic risk measures only except CDSIRFPrd SI and CDSIRFPrd SV. This is consistent with the evidence during the subprime mortgage crisis, which had a long-prolonged effect on the post-crisis periods. In addition, most systemic risk measures in this thesis have also generally shown significant rank correlations between the pre-crisis and the crisis period, and between the pre-crisis period and post-crisis period.

4.5 Structural Break Test

Same to Section 3.4, autoregressive regressions and Quandt-Andrews break point (QABP) tests are carried out to detect the unknown turning points of all the systemic risk measures employed in this thesis. For pairwise risk analysis, structural break dates are tested for both systemic importance and systemic vulnerability of each of the 96 companies in the sample. A break point resulted from one test denotes the quarter when the systemic importance or systemic vulnerability of a firm, indicated by one metric, changed from being in a stable status to an unstable one in the sample priod. For each systemic risk method, frequencies of all significant break quarters are categorised by industry, as exhibited in Figure 16 and Figure 17.

As mentioned in Section 3.4, diverse break points indicated by systemic risk measures, as shown in Figure 16 and Figure 17, suggest that a shock may affect companies in varied levels. Figure 16 illustrates the frequencies of a range of turning quarters for ΔCoRisk and ΔCoVaR, while Figure 17 demonstrates those for DiDe, LRMES and SRISK. If the break quarter with the highest frequency denotes the turning point of a particular measure, as can be seen in Figure 16 and Figure 17, the changing quarters are 2009 Q1 for ΔCoRisk (systemic importance), 2008 Q4 for ΔCoRisk (systemic vulnerability), 2008 Q3, 2009 Q1 and 2009 Q3 for ΔCoVaR (systemic importance), 2009 Q2 for ΔCoVaR (systemic importance), 2011 Q4 for DiDe (systemic importance), 2011 Q4 for DiDe (systemic vulnerablity), 2008 Q3 for LRMES and SRISK. According to the top-frequency bar in each of the four sub-plots, industry composition signifies that generally more banks contributed to risk mode change than insurers and NFIs. Comparison between risk metrics implies that ΔCoVaR (systemic importance), LRMES and SRISK provide earlier risk signals than others. However, if based on the earliest significant break quarter for each of the systemic risk analytics, the turning points are 2008 Q2 for

ΔCoRisk (systemic importance), 2008 Q4 for ΔCoRisk (systemic vulnerability), 2008 Q3 for ΔCoVaR (systemic importance), 2008 Q3 for ΔCoVaR (systemic importance), 2008 Q3 for DiDe (systemic importance), 2008 Q2 for DiDe (systemic vulnerablity), 2008 Q3 for LRMES and SRISK. In terms of the first bar of each of the six sub-plots, roughly more or equal number of insurers transformed their risk patterns, compared with other sectors. With regard to metric contrasts according to the first bars, ΔCoRisk (systemic importance) and DiDe (systemic vulnerablity) transformed their risk status in the same earliest quarter, while all others altered to volatile modes when or after Lehman Brother collapsed. This reveals that CDS-based systemic risk measures provide relatively earlier risk warnings than equity and accounting-based metrics.

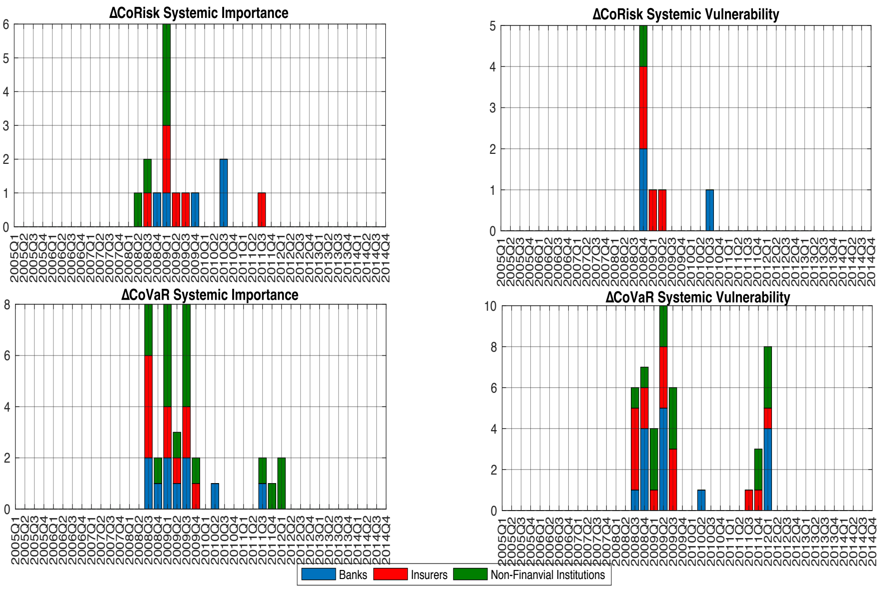

Figure 16 Break Points Frequencies for ΔCoRisk and ΔCoVaR

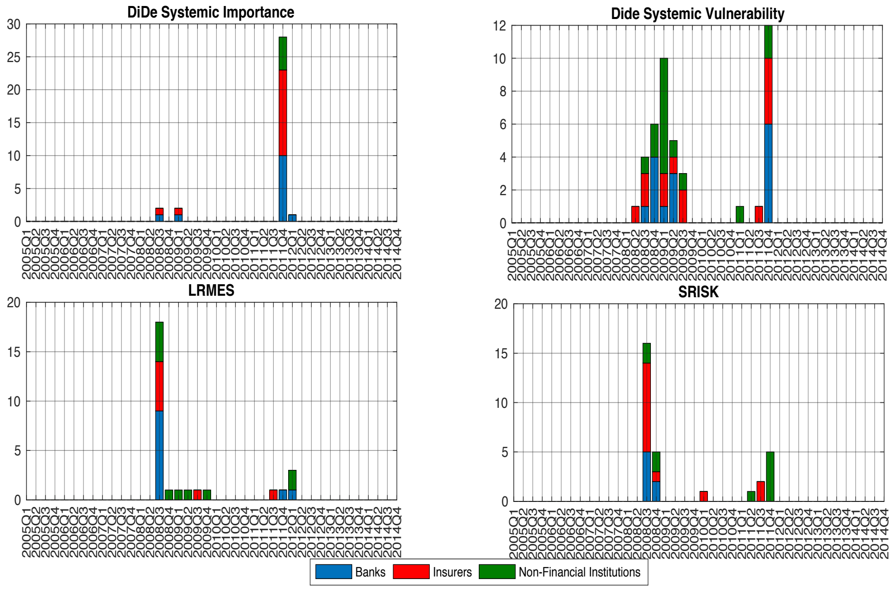

Figure 17 Break Points Frequencies for DiDe, LRMES and SRISK

4.6 Company Risk Ranking

For the aforementioned 40×96 matrix result of each risk methodology, the 96 companies for each quarter are ranked in a descending order. The higher the value of a company, the riskier it is, and the higher position it will be in the risk ranking list. Company risk ranking by the systemic risk methods are listed in the Appendices from Appendix 81 to Table Appendix 92 respectively[31].

Appendix 81 and Appendix 82 are the company risk rankings resulted from $\Delta CoRisk$, whereas the $\Delta CoVaR$ results are in Appendix 83 and Appendix 84. In Appendix 81, $\Delta CoRisk$ identifies the systemic importance of Goldman Sachs and Morgan Stanley in 2008 Q3. Both companies suffered substantially in the financial turmoil. Apart from these two, some others ranked as the first or the second places were recipients of the Troubled Asset Relief Program (TARP)[32] as well: Shinhan Bank, JPMorgan Chase & Co., Credit Suisse and BNP Paribas. Particularly, BNP Paribas was driven to trouble in the very early stage of the distress due to the breakdown of its two hedge funds. With respect to systemic vulnerability in Appendix 82, $\Delta CoRisk$ points out the high riskiness of AIG that is within top three in 2007 Q4, 2008 Q1, 2009 Q2, and especially in 2008 Q4. Table 83 also highlights other greater risk companies throughout the periods such as Intesa Sanpaolo, American Express, Nordea Bank, Lincoln National, all of which were bailed out by TARP. Old Mutual was frequently ranked as number

[31] Only the top 20 risky companies are presented

[32] The TARP program originally authorised a total amount of $700 billion for the rescue. The Dodd-Frank Wall Street Reform and Consumer Protection Act reduced the authorisation to $475 billion.

one, which may be supported by the fact that Old Mutual had counterparty exposures to Lehman Brothers and it struggled with its US division during the financial crash.

Appendix 83 and Appendix 84 have shown the systemic importance and systemic vulnerability of the high risky firms ranked by $\Delta CoVaR$. Appendix 83 ranks UBS AG the most risky one in 2008 Q3. UBS AG was hit hard and was required to seek outside capital from the governments in the subprime mortgage crisis. Some other TARP recipients are recognised as well such as: UniCredit, Bank of America, Intesa Sanpaolo, Lincoln National, Banco Santander, Metlife. Banco Santander is ranked at the second place in 2008 Q4 and in 2009 Q1, which might be due to its loss from the collapse of the Bernard Madoff's Ponzi scheme. Appendix 84 identifies the most famous failures such as MBIA and AIG as top risky, and other troubled companies in the distress such as Radian Group, MGIC, Morgan Stanley, The Hartford, Lincoln National and Citigroup as the first or second risky companies from 2007 Q3 to 2009 Q2. Specifically, these financial institutions were associated with problematic activities and were in trouble in the financial crash: MBIA and Radian Group provided credit enhancement through financial guarantee; MGIC provided mortgage insurance; AIG offered credit protection; Morgan Stanley, The Hartford, Lincoln National and Citigroup suffered huge equity losses.

Appendix 85 and Appendix 86 have displayed the systemic importance and systemic vulnerability of the top 20 risky firms ranked by IRF maximum values respectively. Specifically, in Appendix 85, the impulse (systemic importance) risk ranking using CDS data has shown the higher risk levels of Morgan Stanley and Goldman Sachs in 2008 and 2009. The response (systemic vulnerability) lists attribute the highest risk levels to RBS, Credit Agricole, Intesa Sanpaolo, Aegon N.V., all of which undergone relatively high losses and were bailed out in the crisis periods. In Appendix 86, equity-based IRF analyses recognise JPMorgan Chase & Co., Goldman Sachs, Morgan Stanley, The Hartford, and Bank of America as top systemically important, and Deutsche Bank, UBS AG, UniCredit, and JPMorgan Chase & Co. as most systemically fragile. All of these companies experienced massive losses and obtained bailouts.

The ranking lists resulted from IRF lasting periods are demonstrated in Appendix 87 and Appendix 88. Both tables have listed the risk rankings in 2007, 2008 and 2009. The systemic importance rankings resulted from the CDS-based IRF, as shown in Table 27, has identified the higher risk levels of Radian Group, MGIC, JPMorgan Chase & Co. AIG and Aetna. In the subprime mortgage crisis, Aetna, a health insurance company, cut a large amount of jobs due to the effects of the recession. The systemic vulnerability lists have also shown the top values of Radian Group and Aetna. Equity-based IRF in Appendix 88 presents the highest systemic importance of MGIC and Capital One, and the highest systemic vulnerability of National

Australia and Shinhan Bank. Among these highlighted companies, Capital One suffered from its mortgage platforms and was recapitalised by the US Treasury; National Australia and Shinhan Bank were both the beneficiaries of TARP.

Appendix 89 and Appendix 90 have displayed the firm rankings generated from DiDe. In Appendix 89, DiDe is able to identify the high systemic importance of the well-known troubled firms – BNP Paribas in 2008 Q3, Nordea Bank in 2007 Q4 and Deutsche Bank in 2009 Q1. Loews Corporation is frequently ranked at the first or the second place from 2007 Q3 to 2009 Q2, which could be due to the huge losses in CNA Financial Corp., the subsidiary of Loews Corporation. In Table 30, Radian Group, MGIC, MBIA, AIG and Lincoln National once again were listed at the highest positions as systemically susceptible companies.

Appendix 91 and Appendix 92 exhibit the risk ranking lists assessed by LRMES and SRISK respectively from 2007 Q3 to 2009 Q2. Based on the definitions of LRMES and SRISK, as presented in Section 5.2.2, LRMES and SRISK only capture the systemic vulnerability of companies. In Appendix 91, LRMES recognises Radian Group, MGIC, MBIA, Royal Bank of Scotland (RBS), AIG, Lincoln National, Morgan Stanley, Citigroup, Capital One and The Hartford as firms with highest return losses, while SRISK in Appendix 92 identifies UBS AG, RBS (most frequently ranked as the most risky company by SRISK), Deutsche Bank, Barclays and BNP Paribas as the firms with the greatest capital losses. Back to the financial crash, RBS and Barclays were associated with enormous losses and received bailouts. Both measures could identify some troubled financial institutions in the 2007-2009 financial meltdown, however SRISK emphasises on larger companies relative to LRMES in that SRISK incorporates size as one of its inputs.

4.7 Conclusions

The empirical results from the pairwise sector connectedness plots indicate banks and insurers are strongly connected with each other, but both of them have relatively weak risk connection with NFIs. This is accordance with the evidence of the subprime mortgage crisis. On top of this, systemic risk measures, apart from ΔCoRisk and CDS-based Granger causality tests, signify that banks are the main risk triggers, while insurance companies are the major risk receivers. This is generally consistent with Baluch et al. (2011), Billio et al. (2011); Girardi and Ergün (2013), Chen et al. (2014), and Berdin and Sottocornola (2015). Different from the previous studies, analyses such as ΔCoRisk (CDS-based ΔCoVaR) and CDS-based Granger causality tests in this thesis suggest that insurers were more systemic important than banks during the pre-crisis and the crisis periods. This implies that insurers contribute more credit risk to others, while banks contribute other type of risk (as measured by equity data) to the system. This suggests that insurance companies are associated with higher credit risk, which agrees with hypothesis H4.1. All these observations have been supported by the Conover-Iman tests, which rank risk levels among the 9 pairwise sectors.

Sector risk rankings resulted from Conover-Iman tests have further confirmed the outcome of Conover-Iman tests on sector connectedness: banks are riskier than insurers as the risk contributors, whereas insurance companies are riskier than banks as the risk receivers; banks and insurers are riskier than NFIs.

Results from rank correlation among systemic risk measures have shown that some CDS-based and equity-based systemic risk measures have slightly negative correlation coefficients. This implies that when credit risk of a company is high, risk indicators using equity data may not be able to identify this company as risky. Therefore, as Bisias et al. (2012) and Benoit et al. (2016) suggested, multiple risk measures using diverse information should be considered to produce a better profile of company risk or sector risk. Besides, the systemic importance of a company is distinct from the systemic vulnerability of the company in that these two dimensions of systemic risk have shown slightly negative rank correlation for some risk measures.

Structural break results exhibit that insurance companies switched to a higher risk mode earlier than the other two sectors. By contrast, a greater number of banks experience risk structural changes during the slightly later time period. In addition, CDS-based systemic risk methods provide somewhat earlier risk warning signals than other data-based measures, which is consistent with hypothesis H4.2.

By comparing the firm-level risk analysis and systemic risk analysis, this thesis shows that firm-level risk measures have different sector risk ranking results from systemic risk measures. This agrees with Wagner (2010), López-Espinosa et al. (2013) and Leroy and Lucotte (2017), all of which have found different movements between firm level risk and systemic risk following a change in a common factor. Apart from this, this thesis finds that the results of the firm-level risk measure are consistent to that of systemic vulnerability estimations, whereas different from systemic importance estimations. This may be because pairwise systemic risk, by definition, captures and measures risk from both risk triggers and risk receivers, whereas the standard firm-level risk only estimates the vulnerability of a company.

5 Rank Correlations between the Firm-level Risk Measures and the Systemic Risk Measures and the Ability of Them to Predict Crisis

Policymakers switched regulations from micro-prudential policies to macro-prudential policies since the subprime mortgage crisis in that micro-prudential supervisions based on firm-level risk management failed to mitigate systemic risk. Many previous studies suggest that an appropriate risk regulatory framework should monitor both aggregate risk and firm-level risk by exploring the relationship between firm-level risk and systemic risk. Wagner (2010) claims that there is a negative connection between firm-level risk and systemic risk through diversification where idiosyncratic risk is alleviated, while systemic risk is amplified when firms undertake homogeneous risks. López-Espinosa et al. (2013) find that volatile funding sources lead to rises of both institution-level risk and spillover risk, while trading activities and liquidity management strategies provide contrary effects on firm-level risk and systemic risk. Leroy and Lucotte (2017) suggest that intensive competition encourages banks to undertake more firm-level risks, whereas correlated risk-takings and thus systemic risks are reduced. Section 5.1 in this thesis discovers another one of the relation types between firm-level risk and systemic risk–rank correlation.

Extensive systemic risk measures have been proposed currently, however the question that which one or which few of them perform better is still under discussion. Conducting surveys on manifold systemic risk measures, Bisias et al. (2012) and Benoit et al., (2016) suggest that an ideal risk indicator should contain multi-aspects information and is able to be effective applied for practical purpose. Nevertheless, these two papers haven't recommended any one of the risk metrics to be superior. Rodríguez-Moreno and Peña (2013) and Arsov et al. (2013) have concluded the best-performed systemic risk method, however, they suggest distinct risk measures and neither of them considered SRISK, one of the most popular methodology currently. To fill the gap, this thesis includes SRISK. Since more concerns are on whether it is able to forecast an impending fianncial cisis, Section 5.2 tests the validation of risk measures based on their predictive ability of the crisis. In addition, different from the previous studies, this section classifies the two facets of systemic risk–systemic importance and systemic vulnerability–in the predictive tests to learn whether they have different implications.

The remainder of this section is structured as: Section 5.1 demonstrates the methodology of non-linear correlations and of cross-sectional regressions to predict the subprime mortgage crisis; Section 5.2 presents results and discussions; and Section 5.3 concludes.

5.1 Methodology

This section would like to investigate how firm-level risk measures correlate with systemic risk measures in a non-linear pattern and how these two risk methodologies explain the cross-sectional variation in equity performance and CDS performance during the crisis.

In order to investigate how risk measures predict the subprime mortgage crisis, both firm-level risk and systemic risk methodologies are evaluated in the periods prior to the subprime crisis, i.e., from 2006 Q1 to 2007 Q2 to explain the variation in realised equity and CDS returns during the crash, i.e., from 2007 Q3 to 2008 Q4. For the pairwise systemic risk methodologies, systemic importance and systemic vulnerability are considered separately as independent variables in the regressions. Minimum equity returns (MinEqtRet) are the realised equity returns, and maximum CDS returns (MaxCDSRet) are the realised CDS returns, both of which represent the realised systemic risk during the 2007 financial meltdown. The MinEqtRet (MaxCDSRet) is obtained by using the difference between the minimum stock price (maximum CDS spread) of a company during the crisis period from 2007 Q3 to 2008 Q4 and the equity price (CDS spread) of the firm at the end of 2007 Q2, divided by the company's stock value (CDS spread) at the end of 2007 Q2. For firm-level risk approaches, the maximum values of volatility, VaR, ES, beta and CDS spread, and the minimum value of Z-Score prior to the financial turbulence are computed. Regarding the systemic risk measures, the highest values are required for all of them during the period from 2006 Q1 to 2007 Q2.

In addition to maximum and minimum values, mean values of all dependent variables and independent variables are applied into the regressions for comparison purpose. Specifically, for the measurement of the actual systemic risk in the subprime crisis, mean equity returns (MeanEqtRet) and mean CDS returns (MeanCDSRet) are computed. The MeanEqtRet (MeanCDSRet) is attained by the difference between the average stock price (average CDS spread) of a company during the crisis period from 2007 Q3 to 2008 Q4 and the equity price (CDS spread) of the firm at the end of 2007 Q2, divided by the institution's stock value (CDS spread) at the end of 2007 Q2. Given the popularity of CDS transactions prior to the 2007 financial crisis and the collapse of the CDS market during the crash,

5.1.1 Rank Correlations among Risk Measures

Following Brownlees and Engle (2016), this section selects Spearman's ρ (rank correlation) to assess the non-linear correlation among all the risk indicators in this thesis (firm-level risk measures and systemic risk measures). This section attempts to test the following hypothesis.

H5.1: Firm-level risk is correlated with systemic risk to a large extent.

5.1.2 Risk Measures as Predictors of Equity Performance and CDS Performance during the Crisis

Both Billio et al. (2012) and Acharya et al. (2017) use cross-sectional regression instead of panel regression for prediction analysis. What's more, there is no previous literature using panel regression to analyse system risk measures as predictors of the crisis. So this section employs cross-sectional regression as well. Consistent with Billio et al. (2012), this thesis uses rank regression and has added leverage, market values, and illiquidity as control variables in the cross-sectional regressions as shown in Eq.29.

$$\text{Equity Performance}_i = \alpha + \beta_1 \text{Leverage}_i + \beta_2 \text{Size}_i + \beta_3 \text{Illiquidity}_i + \beta_4 \text{Risk Measure}_{im} + \varepsilon_i$$

$$\text{CDS Performance}_i = \alpha + \beta_1 \text{Leverage}_i + \beta_2 \text{Size}_i + \beta_3 \text{Illiquidity}_i + \beta_4 \text{Risk Measure}_{im} + \varepsilon_i \quad (29)$$

Where *i* represents data of company *i,* and m denotes the m^{th} risk methodology. Leverage is defined as $L_{it} = (D_{it} + W_{it})/W_{it}$, where D_{it} is the book value of debt, W_{it} the market value of equity.The size of a company is its market capitalisation. Following Billio et al. (2012), illiquidity is measured as the first-order autocorrelation of equity returns.

Section 6.3 attempts to test the following hypothesis.

H5.2: CDS-based risk measures are better than non-CDS-based risk measures in terms of the ability to predict the 2007-2009 financial crisis.

5.2 Results and Discussions

5.2.1 Descriptive Statistics

Error! Reference source not found. 93 displays the statistical descriptions of MinEqtRet, MaxCDSRet, and all risk measures in their maximum and minimum values, whie Appendix 94 presents the statistics of MeanEqtRet, MeanCDSRet and all risk measures in their average levels.

5.2.2 Results of Rank Correlations among Risk Measures

Appendix 95 shows the Spearman's correlation coefficients and their statistical significance among the minimum and maximum values of all the risk variables, while Appendix 96 presents the Spearman's correlation and p values among the average levels of all the variables. According to Appendix 95 (Appendix 96), most risk measures are generally negatively related to the MinEqtRet (MeanEqtRet), and are positively related to MaxCDSRet(MeanCDSRet). This is because risk indicators are positively related to risk magnitudes, while a greater value of risk is suggested by lower actual equity returns/higher CDS returns. Z-Score is the only indicator with lower values indicating higher risk, so it has a positive correlation with the MinEqtRet (MeanEqtRet), and a negative relationship with the MaxCDSRet (MeanCDSRet).

In Appendix 95 and Appendix 96, firm-level risk measures have weak correlation (with most Spearman's correlation coefficients lower than 0.4) with all systemic risk measures only except ΔCoVaRSV and LRMES. This denotes that firm-level risk is not able to capture some information reflected only in systemic risk. Size roughly has significant negative correlations with firm-level risk indicators and have significant negative (positive) correlations with the systemic vulnerability (systemic importance) dimension of a systemic risk measure. This means that the bigger the size of a company, the more risk the company contribute to others but the less the company is affected by other companies. This also indirectly implies that, in most cases, firm-level risk tends to positively correlate with the systemic vulnerability dimension of systemic risk.

Except MinEqtRet (MeanEqtRet), Z-Score, and MaxMV (MeanMV), all variables should be positively correlated with each other in theory if the Spearman's correlation are performed on the time series data of them. However, risk measures in this thesis has unbalanced sample sizes in their time series, therefore this study focuses analysis on cross-sectional data. This may be one of the reasons that some negative correlations are shown in the appendices. What's more, these negative values may result from the issue of small sample size.

5.2.3 Results of Cross-Sectional Regressions

Table 8 and Table 9 are the regression analyses based on the max and min values of all the variables. In Table 8, the explained variable is MinEqtRet, the minimum equity returns during the period of 2007 Q3 and 2008 Q4. As can be seen from Table 8, Except CDSs, $\Delta CoRisk$SI, CDSIRFPrdSI, CDSIRFPrdSV, EqtIRFPrdSI, EqtIRFPrdSV, CDSGrangerSI, EqtGrangerSI and DiDeSI, all other risk measures could significantly explain the variation in the realized equity performance of the 96 institutions during the crash. The R-squared statistics suggest that beta (0.629), $\Delta CoVaR$ SI(0.608), $\Delta CoVaR$ SV(0.600), and LRMES(0.606) could explain relatively higher percentage of the variability in MinEqtRet than others.

In Table 9, MaxCDSRet, the maximum CDS returns during the crisis, is the dependent variable. VaR, beta, CDSs, ΔCoRiskSV, ΔCoVaRSI, ΔCoVaRSV, DiDeSV, LRMES and SRISK are able to significantly predict the realized credit risk of the 96 companies in the sample during the crisis. According to R-squared statistics, CDSs (0.380), $\Delta CoVaR$ SI (0.395) and $\Delta CoVaR$SV(0.381) fit a relatively better regression line to explain the variations in the response variable. What's more, both sector dummy and leverage have multicollinearity problem in the regression for SRISK, so both of these two variables are deleted in this particular regression.

In terms of the industry dummies, both tables have shown that most results of insurers are insignificant, while there are more cases where banks and NFIs are significant. Since banks are the “constant”, i.e., the reference category, the results indicate that banks and insurers have little differences in the cross-sectional prediction tests, whereas NFIs are distinct from the other two sectors. This makes sense as both banks and insurers are financial institutions that share some similar characteristics.

Another finding is that Size in Table 8 is insignificant in all regressions where MinEqtRet is the dependent variable (this is consistent with Billio et al. (2012), while it is significant in Table 9 in most regressions with MaxCDSRet as the explained variable. This suggests that the size of a company will not decide the equity performance of this company, whereas it matters more for credit risk movements of the company.

Table 8 Rank Regressions with MinEqtRet, the Minimum Realised Equity Return during the Crisis, as the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Size	-0.0610	-0.0621	-0.0744	-0.0318	-0.0105	0.0610	0.0322	0.108
	(0.114)	(0.110)	(0.113)	(0.105)	(0.122)	(0.114)	(0.115)	(0.116)
Illiquidity	-0.384***	-0.402***	-0.388***	-0.422***	-0.386***	-0.403***	-0.379***	-0.368***
	(0.0742)	(0.0736)	(0.0725)	(0.0732)	(0.0792)	(0.0795)	(0.0787)	(0.0762)
Volatility	-0.195***							
	(0.0737)							
VaR		-0.207***						
		(0.0724)						
ES			-0.224***					
			(0.0718)					
Beta				-0.351***				
				(0.0696)				
CDSs					-0.121			
					(0.0748)			
Z-Score						0.228**		
						(0.0892)		
$\Delta CoRisk$SI							0.114	
							(0.0781)	
$\Delta CoRisk$SV								-0.186**
								(0.0750)
Sector								
Insurers	7.312	7.535	6.197	6.429	12.14*	20.92***	12.73**	6.572
	(6.431)	(6.300)	(6.280)	(5.679)	(6.548)	(7.489)	(6.389)	(6.370)
NFIs	30.78***	30.50***	30.21***	26.35***	33.09***	31.29***	31.10***	27.53***
	(4.936)	(4.937)	(4.929)	(5.113)	(5.170)	(5.040)	(5.011)	(4.940)
Constant	66.83***	68.35***	69.69***	76.63***	58.54***	36.63***	45.19***	58.76***
	(10.08)	(10.10)	(10.04)	(9.359)	(10.71)	(10.92)	(9.425)	(8.829)
Observations	96	96	96	96	96	96	96	96
R-squared	0.548	0.552	0.558	0.629	0.529	0.542	0.529	0.544

(continued)

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Size	0.0689	-0.00816	0.100	0.114	0.0523	0.0453	0.0752	0.112
	(0.105)	(0.105)	(0.117)	(0.117)	(0.115)	(0.115)	(0.108)	(0.113)
Illiquidity	-0.422***	-0.420***	-0.402***	-0.396***	-0.376***	-0.360***	-0.378***	-0.422***
	(0.0728)	(0.0721)	(0.0754)	(0.0818)	(0.0812)	(0.0810)	(0.0781)	(0.0827)
$\Delta CoVaR$SI	-0.349***							
	(0.0743)							
$\Delta CoVaR$SV		-0.337***						
		(0.0786)						
CDSIRFMaxSI			-0.235***					
			(0.0823)					
CDSIRFMaxSV				-0.268***				
				(0.0944)				
CDSIRFPrdSI					0.000197			
					(0.0737)			
CDSIRFPrdSV						-0.0806		
						(0.0683)		
EqtIRFMaxSI							-0.172**	
							(0.0742)	
EqtIRFMaxSV								-0.214***
								(0.0778)
Sector								
Insurers	7.014	5.192	10.76	11.51*	10.81	10.50	11.69*	9.293
	(5.858)	(5.991)	(6.478)	(6.410)	(6.614)	(6.595)	(6.166)	(5.901)
NFIs	19.10***	20.53***	22.70***	21.70***	32.01***	32.17***	28.22***	24.62***
	(5.453)	(5.756)	(5.682)	(5.918)	(5.171)	(5.194)	(5.492)	(5.977)
Constant	73.86***	77.03***	63.38***	64.12***	49.91***	53.45***	58.25***	62.63***
	(8.445)	(9.434)	(8.740)	(9.087)	(9.577)	(10.00)	(8.764)	(9.140)
Observations	96	96	96	96	96	96	96	96
R-squared	0.608	0.600	0.556	0.567	0.519	0.525	0.545	0.553

(continued)

	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)
Size	0.0541	0.0508	0.0495	0.104	0.0671	0.103	0.136	-0.00936	-0.00395	-0.0276
	(0.113)	(0.114)	(0.114)	(0.107)	(0.111)	(0.112)	(0.137)	(0.105)	(0.105)	(0.109)
Illiquidity	-0.395***	-0.376***	-0.377***	-0.416***	-0.408***	-0.399***	-0.372***	-0.398***	-0.403***	-0.378***
	(0.0794)	(0.0817)	(0.0799)	(0.0771)	(0.0816)	(0.0814)	(0.0814)	(0.0779)	(0.0713)	(0.0750)
EqtIRFPrdSI	0.110									
	(0.0766)									
EqtIRFPrdSV		0.00866								
		(0.0754)								
CDSGrangerSI			0.0116							
			(0.0879)							
CDSGrangerSV				-0.296***						
				(0.0800)						
EqtGrangerSI					0.129					
					(0.0800)					
EqtGgrangerSV						-0.143**				
						(0.0697)				
DiDeSI							-0.135			
							(0.0841)			
DiDeSV								-0.305***		
								(0.0704)		
LRMES									-0.335***	
									(0.0757)	
SRISK										-0.427***
										(0.129)
Sector										
Insurers	11.66*	10.72	10.79	13.27**	13.03**	13.09**	10.76*	14.43**	4.616	3.494
	(6.535)	(6.609)	(6.643)	(6.153)	(6.410)	(6.267)	(6.447)	(6.107)	(5.833)	(5.535)
NFIs	32.76***	32.03***	32.30***	24.24***	34.68***	32.61***	29.09***	27.99***	21.98***	11.34
	(5.309)	(5.126)	(5.881)	(5.088)	(5.606)	(5.123)	(5.576)	(4.745)	(5.358)	(8.533)
Constant	44.91***	49.62***	49.43***	65.52***	42.84***	54.57***	53.20***	68.90***	75.59***	83.91***
	(9.716)	(9.594)	(10.72)	(8.713)	(10.26)	(9.256)	(8.990)	(8.800)	(9.195)	(11.07)
Observations	96	96	96	96	96	96	96	96	96	96
R-squared	0.530	0.519	0.519	0.590	0.532	0.536	0.532	0.589	0.606	0.585

This table displays the outcomes of the cross-sectional regressions of the realised minimum equity returns (MinEqtRet) during the period from 2007 Q3 to 2008 Q4, on the maximum or minimum values of the risk measures during the period of 2006 Q1 to 2007Q2. Leverage is defined as $L_{it} = (D_{it} + W_{it})/W_{it}$, where D_{it} is the book value of debt, W_{it} the market value of equity. The size of a company is its market capitalisation. Illiquidity is measured as the first-order autocorrelation of equity returns. VaR is the 95th percentile. CDSs is the CDS spread. The suffix of "SI" of the systemic risk measures means the systemic importance of the firms. the suffix of "SV" of the systemic risk measures means the systemic vulnerability of the firms. "~IRFMax~" refers to the IRF results based on the maximum values of the impulse response plots. "~IRFPrd~"refers to the IRF results based on the lasting periods in the impulse response plots. Robust standard errors are in parentheses, and they are to remedy the problem of autocorrelation and heteroscedasticity. Variance Inflation Factors (VIF) has been performed to test multicollinearity. Control variables that have multicollinearity with other variables are removed one by one until no multicollinearity exists. ***, **, and * indicate significance at 1%,5%, and 10% respectively.

Table 9 Rank Regressions with MaxCDSRet, the Maximum Realised CDS Return during the Crisis, as the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Size	0.310**	0.366***	0.330***	0.307***	0.101	0.268***	0.282***	0.199*
	(0.127)	(0.121)	(0.124)	(0.109)	(0.112)	(0.0989)	(0.100)	(0.101)
Illiquidity	0.404***	0.424***	0.407***	0.425***	0.373***	0.383***	0.403***	0.391***
	(0.0884)	(0.0886)	(0.0876)	(0.0877)	(0.0896)	(0.0923)	(0.0870)	(0.0844)
Volatility	0.0820							
	(0.102)							
VaR		0.188*						
		(0.104)						
ES			0.120					
			(0.104)					
Beta				0.188**				
				(0.0859)				
CDSs					-0.312***			
					(0.0969)			
Z-Score						0.142		
						(0.105)		
$\Delta CoRisk$SI							-0.113	
							(0.117)	
$\Delta CoRisk$SV								0.212**
								(0.104)
Sector								
Insurers	4.449	5.961	5.453	5.326	6.398	9.268	1.070	7.797
	(6.244)	(6.195)	(6.274)	(6.472)	(6.635)	(7.525)	(6.377)	(6.578)
NFIs	-19.50***	-18.64***	-19.05***	-16.98***	-17.25***	-20.47***	-19.11***	-14.93**
	(6.076)	(6.209)	(6.075)	(6.142)	(6.377)	(6.180)	(6.031)	(6.262)
Constant	14.93	5.263	11.44	7.729	44.26***	13.78	26.76***	12.01
	(12.13)	(12.57)	(12.15)	(10.91)	(9.696)	(9.851)	(9.126)	(9.248)
Observations	96	96	96	96	96	96	96	96
R-squared	0.320	0.343	0.326	0.347	0.380	0.324	0.325	0.348

(continued)

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Size	0.247**	0.317***	0.246**	0.260**	0.262**	0.272***	0.248**	0.245**
	(0.104)	(0.110)	(0.105)	(0.102)	(0.100)	(0.0987)	(0.103)	(0.103)
Illiquidity	0.444***	0.440***	0.409***	0.401***	0.402***	0.378***	0.401***	0.414***
	(0.0844)	(0.0858)	(0.0904)	(0.0897)	(0.0895)	(0.0912)	(0.0885)	(0.0934)
$\Delta CoVaR$SI	0.330***							
	(0.0983)							
$\Delta CoVaR$SV		0.303***						
		(0.0994)						
CDSIRFMaxSI			0.0779					
			(0.127)					
CDSIRFMaxSV				0.0109				
				(0.115)				
CDSIRFPrdSI					-0.0395			
					(0.0787)			
CDSIRFPrdSV						0.110		
						(0.0943)		
EqtIRFMaxSI							0.104	
							(0.0875)	
EqtIRFMaxSV								0.0631
								(0.0998)
Sector								
Insurers	6.566	8.039	2.990	2.945	2.865	3.399	2.444	3.421
	(6.564)	(6.447)	(6.319)	(6.263)	(6.233)	(6.316)	(6.484)	(6.381)
NFIs	-7.807	-9.678	-16.93*	-19.60**	-19.60***	-20.23***	-17.73***	-17.85**
	(6.722)	(6.599)	(8.673)	(7.647)	(5.932)	(6.041)	(6.555)	(7.203)
Constant	-0.578	-2.373	17.60	21.48*	23.77***	17.26*	17.04*	18.32*
	(11.12)	(11.44)	(11.44)	(10.89)	(8.579)	(9.099)	(9.208)	(10.59)
Observations	96	96	96	96	96	96	96	96
R-squared	0.395	0.381	0.319	0.315	0.317	0.327	0.325	0.318

(continued)

	(17)	(18)	(19)	(20)	(22)	(22)	(23)	(24)	(25)	(26)
Size	0.261**	0.285***	0.248**	0.256**	0.281***	0.285***	0.217*	0.204**	0.302***	0.168*
	(0.101)	(0.0941)	(0.103)	(0.103)	(0.104)	(0.106)	(0.119)	(0.0926)	(0.108)	(0.0995)
Illiquidity	0.414***	0.410***	0.397***	0.405***	0.359***	0.389***	0.398***	0.379***	0.419***	0.449***
	(0.0901)	(0.0885)	(0.0888)	(0.0912)	(0.0903)	(0.0921)	(0.0894)	(0.0882)	(0.0853)	(0.0943)
EqtIRFPrdSI	-0.0817									
	(0.0868)									
EqtIRFPrdSV		-0.138								
		(0.0918)								
CDSGrangerSI			0.0612							
			(0.108)							
CDSGrangerSV				0.0368						
				(0.113)						
EqtGrangerSI					0.166					
					(0.104)					
EqtGrangerSV						-0.0645				
						(0.0900)				
DiDeSI							0.0733			
							(0.100)			
DiDeSV								-0.290***		
								(0.0986)		
LRMES									0.237**	
									(0.0984)	
SRISK										0.210**
										(0.103)
Sector										
Insurers	2.342	4.467	2.826	2.668	5.828	4.002	3.002	6.412	7.352	
	(6.306)	(6.122)	(6.244)	(6.334)	(6.285)	(6.231)	(6.414)	(5.975)	(6.537)	
NFIs	-20.58***	-20.27***	-18.48**	-19.05***	-16.58**	-19.75***	-18.44***	-23.84***	-12.93*	
	(6.041)	(5.817)	(7.290)	(7.102)	(6.613)	(6.131)	(6.542)	(5.828)	(6.559)	
Constant	25.79***	26.74***	19.50*	20.12*	12.95	24.16***	20.28**	40.11***	3.917	8.398
	(9.675)	(8.733)	(10.36)	(10.54)	(10.62)	(8.704)	(8.872)	(8.040)	(11.40)	(8.744)
Observations	96	96	96	96	96	96	96	96	96	96
R-squared	0.321	0.334	0.318	0.316	0.337	0.319	0.319	0.378	0.359	0.259

This table displays the outcomes of the cross-sectional regressions of the realised maximum CDS returns (MaxCDSRet) during the period from 2007 Q3 to 2008 Q4, on the maximum or minimum values of the risk measures during the period of 2006 Q1 to 2007Q2. Leverage is defined as $L_{it} = (D_{it} + W_{it})/W_{it}$, where D_{it} is the book value of debt, W_{it} the market value of equity. The size of a company is its market capitalisation. Illiquidity is measured as the first-order autocorrelation of equity returns. VaR is the 95th percentile. CDSs is the CDS spread. the suffix of "SI" of the systemic risk measures means the systemic importance of the firms. the suffix of "SV" of the systemic risk measures means the systemic vulnerability of the firms. "~IRFMax~" refers to the IRF results based on the maximum values of the impulse response plots. "~IRFPrd~"refers to the IRF results based on the lasting periods in the impulse response plots. Robust standard errors are in parentheses, and they are to remedy the problem of autocorrelation and heteroscedasticity. Variance Inflation Factors (VIF) has been performed to test multicollinearity. Control variables that have multicollinearity with other variables are removed one by one until no multicollinearity exists. ***, **, and * indicate significance at 1%,5%, and 10% respectively.

Table 10 and Table 11 are the regression analyses based on the average levels of all the variables. In Table 10, the explained variable is MeanEqtRet, the mean equity returns during the period of 2007 Q3 and 2008 Q4. As can be seen from Table 10, volatility, VaR, ES, beta, $\Delta CoVaR$SI, $\Delta CoVaR$SV, CDSIRFMaxSI, CDSIRFMaxSV, EqtIRFMaxSI, EqtIRFPrdSI, CDSGrangerSV, DiDeSV, LRMES and SRISK could significantly explain the realized equity performance of the 96 institutions during the crash. The R-squared statistics suggest that beta (0.534) and $\Delta CoVaR$SI (0.508) could explain relatively higher percentage of the variability in MeanEqtRet than others.

In Table 11, MeanCDSRet, the mean CDS returns during the crisis, is the dependent variable. VaR, CDSs, $\Delta CoRisk$ SV, EqtGrangerSI, EqtGrangerSV, DiDeSV, LRMES and SRISK are significant to predict the realized credit risk of the 96 companies in the sample during the crisis. According to R-squared statistic, $\Delta CoRisk$SV (0.569) fits the best regression line to explain the variation in the response variable. Both sector dummy and leverage have multicollinearity problem in the regression for SRISK, so both of these two variables are deleted in this particular regression.

Insurers are insignificant for most regressions, while banks and NFIs are significant in a majority of cases. Given that the banking sector is the reference category, the results confirm that banks and insurers are the same in terms of forecasting crisis, however NFIs are distinct from these two financial sectors.

Similar to the observations from Table 8 and Table 9, Size in Table 10 is insignificant in all regressions, while it is significant in majority of regressions in Table 11. Therefore the same conclusion is obtained that the size of a company does not explain its equity performance very well, but it affects the company's credit risk.

Table 10 Rank Regressions with MeanEqtRet, the Mean Value of Realised Equity Returns during the Crisis, as the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Size	-0.113	-0.123	-0.131	-0.0535	-0.0409	0.00723	-0.0236	0.0318
	(0.131)	(0.126)	(0.129)	(0.120)	(0.142)	(0.137)	(0.138)	(0.141)
Illiquidity	-0.350***	-0.364***	-0.352***	-0.391***	-0.344***	-0.367***	-0.341***	-0.316***
	(0.0795)	(0.0787)	(0.0781)	(0.0753)	(0.0880)	(0.0811)	(0.0862)	(0.0828)
Volatility	-0.159**							
	(0.0778)							
VaR		-0.188**						
		(0.0777)						
ES			-0.201***					
			(0.0712)					
Beta				-0.371***				
				(0.0802)				
CDSs					-0.0423			
					(0.0933)			
Z-Score						0.164		
						(0.105)		
$\Delta CoRisk$SI							0.0252	
							(0.0789)	
$\Delta CoRisk$SV								-0.127
								(0.102)
Sector								
Insurers	7.608	7.447	6.335	6.813	10.79	15.27*	10.78	10.05
	(7.269)	(7.209)	(7.225)	(6.571)	(7.671)	(8.437)	(7.662)	(7.776)
NFIs	29.51***	29.23***	28.99***	20.67***	30.82***	27.23***	30.61***	26.12***
	(5.636)	(5.639)	(5.564)	(6.124)	(5.844)	(6.038)	(5.836)	(6.380)
Constant	66.30***	69.01***	69.88***	78.88***	55.35***	43.86***	51.16***	56.41***
	(11.34)	(10.92)	(10.92)	(10.21)	(13.49)	(13.55)	(11.69)	(11.79)
Observations	96	96	96	96	96	96	96	96
R-squared	0.438	0.446	0.450	0.534	0.420	0.435	0.420	0.430

(continued)

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Size	0.0630	-0.0448	0.0400	0.0558	-0.00426	-0.00876	-0.000887	0.0266
	(0.127)	(0.120)	(0.131)	(0.139)	(0.137)	(0.134)	(0.126)	(0.138)
Illiquidity	-0.386***	-0.401***	-0.355***	-0.345***	-0.345***	-0.352***	-0.332***	-0.361***
	(0.0803)	(0.0751)	(0.0794)	(0.0845)	(0.0838)	(0.0815)	(0.0805)	(0.0849)
$\Delta CoVaR$SI	-0.326***							
	(0.0796)							
$\Delta CoVaR$SV		-0.352***						
		(0.0730)						
CDSIRFMaxSI			-0.332***					
			(0.0886)					
CDSIRFMaxSV				-0.286***				
				(0.105)				
CDSIRFPrdSI					0.0883			
					(0.0815)			
CDSIRFPrdSV						0.121		
						(0.0878)		
EqtIRFMaxSI							-0.238***	
							(0.0810)	
EqtIRFMaxSV								-0.152
								(0.0947)
Sector								
Insurers	10.14	8.330	9.704	10.77	11.11	11.62	10.63	9.821
	(6.632)	(6.629)	(7.063)	(7.056)	(7.802)	(7.740)	(7.042)	(7.116)
NFIs	21.48***	21.05***	18.45***	18.65**	29.61***	29.78***	26.08***	26.32***
	(5.972)	(5.898)	(6.710)	(7.297)	(5.939)	(5.920)	(5.843)	(6.525)
Constant	69.42***	77.38***	70.48***	66.61***	47.59***	46.24***	63.93***	60.01***
	(9.915)	(9.594)	(11.02)	(10.49)	(12.55)	(13.01)	(10.78)	(10.80)
Observations	96	96	96	96	96	96	96	96
R-squared	0.508	0.521	0.498	0.468	0.427	0.433	0.470	0.438

(continued)

	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)
Size	-0.0357	-0.00819	-0.0352	0.0319	-0.0114	0.0111	0.0486	-0.0704	-0.0677	-0.0968
	(0.126)	(0.131)	(0.136)	(0.128)	(0.136)	(0.138)	(0.160)	(0.128)	(0.125)	(0.128)
Illiquidity	-0.354***	-0.366***	-0.344***	-0.378***	-0.351***	-0.351***	-0.335***	-0.364***	-0.364***	-0.342***
	(0.0780)	(0.0830)	(0.0860)	(0.0832)	(0.0887)	(0.0873)	(0.0871)	(0.0878)	(0.0747)	(0.0790)
EqtIRFPrdSI	0.208**									
	(0.0803)									
EqtIRFPrdSV		0.129								
		(0.0832)								
CDSGrangerSI			0.0841							
			(0.0898)							
CDSGrangerSV				-0.295***						
				(0.0848)						
EqtGrangerSI					0.0477					
					(0.0883)					
EqtGangerSV						-0.0790				
						(0.0762)				
DiDeSI							-0.0996			
							(0.0969)			
DiDeSV								-0.244***		
								(0.0800)		
LRMES									-0.296***	
									(0.0775)	
SRISK										-0.433***
										(0.130)
Sector										
Insurers	9.798	10.12	10.25	12.74*	11.21	11.63	10.54	12.52*	4.919	3.062
	(6.833)	(7.267)	(7.661)	(7.025)	(7.650)	(7.600)	(7.533)	(7.269)	(6.870)	(6.890)
NFIs	27.18***	31.04***	32.66***	22.85***	31.55***	30.89***	28.10***	26.77***	21.71***	9.581
	(6.122)	(5.912)	(5.908)	(5.910)	(6.129)	(5.814)	(6.368)	(6.009)	(6.057)	(8.980)
Constant	45.01***	46.66***	48.50***	67.70***	49.49***	54.67***	54.34***	68.34***	74.91***	86.57***
	(10.88)	(12.27)	(11.88)	(10.69)	(12.18)	(11.54)	(10.92)	(11.57)	(10.36)	(13.06)
Observations	96	96	96	96	96	96	96	96	96	96
R-squared	0.459	0.434	0.425	0.490	0.421	0.425	0.426	0.464	0.487	0.488

This table displays the outcomes of the cross-sectional regressions of the realised mean equity returns (MeanEqtRet) during the period from 2007 Q3 to 2008 Q4, on the mean values of the risk measures during the period of 2006 Q1 to 2007Q2. Leverage is defined as $L_{it} = (D_{it} + W_{it})/W_{it}$, where D_{it} is the book value of debt, W_{it} the market value of equity. The size of a company is its market capitalisation. Illiquidity is measured as the first-order autocorrelation of equity returns. VaR is the 95th percentile. CDSs is the CDS spread. the suffix of "SI" of the systemic risk measures means the systemic importance of the firms. the suffix of "SV" of the systemic risk measures means the systemic vulnerability of the firms. "~IRFMax~" refers to the IRF results based on the maximum values of the impulse response plots. "~IRFPrd~"refers to the IRF results based on the lasting periods in the impulse response plots. Robust standard errors are in parentheses, and they are to remedy the problem of autocorrelation and heteroscedasticity. Variance Inflation Factors (VIF) has been performed to test multicollinearity. Control variables that have multicollinearity with other variables are removed one by one until no multicollinearity exists. ***, **, and * indicate significance at 1%,5%, and 10% respectively.

Table 11 Regressions with MeanCDSRet, the Mean Value of the Realised CDS Returns during the Crisis, as the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Size	0.394***	0.419***	0.375***	0.306***	0.0986	0.308***	0.288***	0.0807
	(0.121)	(0.117)	(0.119)	(0.0984)	(0.104)	(0.0949)	(0.102)	(0.0884)
Illiquidity	0.400***	0.418***	0.398***	0.404***	0.346***	0.375***	0.386***	0.290***
	(0.0807)	(0.0796)	(0.0812)	(0.0851)	(0.0824)	(0.0880)	(0.0851)	(0.0720)
Volatility	0.164							
	(0.104)							
VaR		0.220**						
		(0.101)						
ES			0.139					
			(0.102)					
Beta				0.110				
				(0.0908)				
CDSs					-0.347***			
					(0.0911)			
Z-Score						0.0811		
						(0.110)		
$\Delta CoRisk$SI							0.0290	
							(0.107)	
$\Delta CoRisk$SV								0.561***
								(0.0961)
Sector								
Insurers	5.559	6.150	5.508	3.756	5.982	5.109	3.139	4.213
	(6.018)	(5.994)	(6.124)	(6.038)	(5.927)	(6.787)	(5.823)	(5.640)
NFIs	-23.68***	-23.19***	-23.66***	-21.83***	-22.67***	-26.41***	-24.71***	-5.176
	(5.540)	(5.594)	(5.501)	(5.965)	(5.440)	(5.696)	(5.548)	(6.511)
Constant	8.087	2.858	10.36	14.75	49.33***	18.59*	21.57**	3.670
	(12.28)	(12.19)	(11.96)	(10.56)	(9.835)	(9.579)	(8.307)	(8.903)
Observations	96	96	96	96	96	96	96	96
R-squared	0.383	0.401	0.378	0.374	0.439	0.368	0.364	0.569

(continued)

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Size	0.279***	0.301***	0.281***	0.246**	0.295***	0.293***	0.292***	0.310***
	(0.0973)	(0.0975)	(0.0972)	(0.105)	(0.0948)	(0.0966)	(0.0958)	(0.1000)
Illiquidity	0.398***	0.400***	0.393***	0.393***	0.389***	0.393***	0.387***	0.381***
	(0.0878)	(0.0855)	(0.0848)	(0.0865)	(0.0864)	(0.0844)	(0.0846)	(0.0871)
$\Delta CoVaR$SI	0.0684							
	(0.0904)							
$\Delta CoVaR$SV		0.0660						
		(0.0861)						
CDSIRFMaxSI			0.0863					
			(0.121)					
CDSIRFMaxSV				0.197				
				(0.123)				
CDSIRFPrdSI					-0.00288			
					(0.0946)			
CDSIRFPrdSV						-0.0396		
						(0.0771)		
EqtIRFMaxSI							0.0502	
							(0.0781)	
EqtIRFMaxSV								-0.0499
								(0.0911)
Sector								
Insurers	2.749	3.084	2.876	2.435	2.674	2.294	2.646	2.510
	(6.006)	(6.031)	(5.993)	(5.938)	(5.921)	(5.869)	(5.984)	(5.948)
NFIs	-22.85***	-22.97***	-21.61***	-16.55**	-24.72***	-24.50***	-23.81***	-26.15***
	(6.198)	(5.964)	(7.613)	(8.137)	(5.779)	(5.599)	(5.845)	(6.303)
Constant	19.03*	17.93*	17.90*	12.68	22.82***	24.59***	20.18**	25.27***
	(9.657)	(10.29)	(10.69)	(10.58)	(7.789)	(8.456)	(8.853)	(9.382)
Observations	96	96	96	96	96	96	96	96
R-squared	0.368	0.367	0.369	0.387	0.364	0.365	0.366	0.366

(continued)

	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)
Size	0.306***	0.297***	0.273***	0.285***	0.324***	0.350***	0.251**	0.224***	0.331***	0.195*
	(0.0953)	(0.0965)	(0.0963)	(0.0985)	(0.0995)	(0.102)	(0.122)	(0.0851)	(0.101)	(0.102)
Illiquidity	0.397***	0.385***	0.382***	0.397***	0.328***	0.364***	0.386***	0.355***	0.406***	0.443***
	(0.0815)	(0.0886)	(0.0843)	(0.0895)	(0.0825)	(0.0864)	(0.0854)	(0.0795)	(0.0814)	(0.0903)
EqtIRFPrdSI	-0.118									
	(0.0884)									
EqtIRFPrdSV		0.0151								
		(0.0946)								
CDSGrangerSI			0.106							
			(0.106)							
CDSGrangerSV				0.0656						
				(0.116)						
EqtGrangerSI					0.249**					
					(0.0962)					
EqtGrangerSV						-0.154*				
						(0.0848)				
DiDeSI							0.0678			
							(0.101)			
DiDeSV								-0.328***		
								(0.0936)		
LRMES									0.209**	
									(0.0972)	
SRISK										0.278***
										(0.0948)
Sector										
Insurers	3.034	2.666	2.520	2.175	6.954	5.117	2.599	5.543	6.549	
	(5.988)	(5.945)	(5.939)	(5.921)	(5.856)	(5.797)	(5.985)	(5.476)	(6.219)	
NFIs	-22.84***	-24.70***	-22.12***	-23.04***	-19.61***	-24.12***	-23.08***	-29.84***	-18.52***	
	(5.697)	(5.503)	(6.615)	(6.843)	(5.643)	(5.421)	(6.699)	(5.102)	(6.314)	
Constant	26.69***	22.03**	18.14*	19.19*	8.999	27.66***	21.15**	44.41***	6.619	4.039
	(8.412)	(8.895)	(9.724)	(10.90)	(9.661)	(8.406)	(8.561)	(8.411)	(11.65)	(8.909)
Observations	96	96	96	96	96	96	96	96	96	96
R-squared	0.376	0.364	0.373	0.367	0.412	0.384	0.367	0.445	0.397	0.289

This table displays the outcomes of the cross-sectional regressions of the realised mean CDS returns (MeanCDSRet) during the period from 2007 Q3 to 2008 Q4, on the mean values of the risk measures during the period of 2006 Q1 to 2007Q2. Leverage is defined as $L_{it} = (D_{it} + W_{it})/W_{it}$, where D_{it} is the book value of debt, W_{it} the market value of equity. The size of a company is its market capitalisation. Illiquidity is measured as the first-order autocorrelation of equity returns. VaR is the 95th percentile. CDSs is the CDS spread. the suffix of "SI" of the systemic risk measures means the systemic importance of the firms. the suffix of "SV" of the systemic risk measures means the systemic vulnerability of the firms. "~IRFMax~" refers to the IRF results based on the maximum values of the impulse response plots. "~IRFPrd~"refers to the IRF results based on the lasting periods in the impulse response plots. Robust standard errors are in parentheses, and they are to remedy the problem of autocorrelation and heteroscedasticity. Variance Inflation Factors (VIF) has been performed to test multicollinearity. Control variables that have multicollinearity with other variables are removed one by one until no multicollinearity exists. ***, **, and * indicate significance at 1%,5%, and 10% respectively.

5.3 Conclusions

Results from Spearman's correlation have revealed that the firm-level risk indicators in this thesis are weakly correlated with most of the systemic risk measures (generally consistent with Wagner, 2010, López-Espinosa et al. 2013, and Leroy and Lucotte, 2017). This signifies that firm-level risk could explain systemic risk to some extent, nevertheless there are other facets in systemic risk that are not reflected in firm-level risk. This is against the hypothesis H5.1. A new finding in this thesis is that firm-level risk correlates more to the systemic vulnerability than to the systemic importance of systemic risk, which means that firm-level risk tends more to capture a firm's fragility when the firm is affected by others.

Empirical results from cross-sectional regressions show that DiDeSV, LRMES and SRISK are statistically significant at 5 per cent in all regressions with MinEqtRet, MaxCDSRet, MeanEqtRet and MeanCDSRet as the dependent variable respectively. This is different from what hypothesis H5.2 expects that the CDS-based risk measures will perform better in predicting the crisis. In terms of the firm-level risk measures, none of them could significantly explain all of the four dependent variables, with VaR and beta being significant in three regressions at 5 percent. This supports that the macro-prudential regulatory frameworks should emphasise on the systemic risk indicators and use the standard risk measures such as VaR and beta as complementary.

6 Concluding Remarks

This thesis applies both firm-level risk measures and systemic risk measures on different sectors using both CDS data and non-CDS data. Different from previous literature, this research has included firm-level risk measures in addition to systemic risk measures to investigate risk of insurers relative to banks and NFIs. Besides, this thesis is the first one that adopts relatively comprehensive and widely cited risk methodologies to compare CDS-based and non-CDS based risk measures. Moreover, impulse response function (IRF) is proposed in this study to quantify systemic risk. There is also rare previous research using statistical significance tests following the systemic risk analysis, this study fills this gap by applying the significance test (Wilcoxon signed-rank test) as well as dominance test (Conover-Iman test) on both firm-level risk assessments and systemic risk assessments. Last but not least, the systemic importance and systemic vulnerability of a company are analysed separately to reflect the two dimensions of systemic risk, which has not been researched on by many existing studies.

The aim of this thesis is trying to solve the following issues: (1) the risk level of insurance companies in the 2007-2009 financial crisis relative to banks and NFIs; (2) the role of the CDS data in assessing risks in comparison with non-CDS data; (3) the association between firm-level risk and systemic risk; and (4) the performance of the risk measures on predicting the subprime mortgage crisis.

Results from sector connectedness analysis disclose that banks and insurers have stronger connections between each other, while both of them have relatively lower level of connections with NFIs (in line with Billio et al. (2011)). Besides, this thesis finds that banks are the main risk triggers that contribute more risk to others, while insurance companies are the major risk receivers that are affected most by others. This agrees with Baluch et al. (2011), Billio et al. (2011); Girardi and Ergün (2013), Chen et al. (2014), and Berdin and Sottocornola (2015). There are also new findings in this thesis, i.e. Firm-level risk analysis (systemic risk analysis) suggest that insurers are riskier than other sectors in terms of credit risk (insurers contribute more credit risk to others), while banks are riskier in terms of equity-based risk (banks contribute more equity-based risk to the system).

Regarding the role of data source in risk analysis, first, CDS-based and non-CDS based risk indicators have shown different risk ranking results among banks and insurers, signifying that more types of data should be considered together to have a more comprehensive risk profile of a company/sector. Second, structural break tests on both firm-level risk assessments and systemic risk assessments suggest that the CDS-sourced risk switched to the crisis mode at earlier stage, if compared with the equity-based and accounting-based risk. This implies that credit risk of a company provides early-warning signals of crisis and regulatory bodies should pay more attention to credit risk changes.

Rank correlations between firm-level risk measures and systemic risk measures show that firm-level risk cannot capture some factors that are only measured by systemic risk, therefore macro-prudential policies emphasizing on systemic risk methodologies are necessary. In addition, firm-level risk results are more associated with the systemic vulnerability of systemic risk, implying that the firm-level risk of a company approximately represents the vulnerability of the company as a risk receiver.

The cross-sectional regressions show that DiDeSV, LRMES and SRISK, all of which are systemic risk measures, are the most outstanding risk indicators as compared with firm-level risk measures and other systemic risk methodologies.

The limitation of this thesis stems from data restrictions. Limited CDS data confines the sample to 96 companies, i.e. 32 members in each of the three sectors. What's more, since CDS data has less variations in the early quarters of the sample, Granger-causality tests and IRF are on annual basis rather than quarterly basis as for other risk measures. This makes comparisons across risk measures difficult in that risk indicators have different sample sizes.

Future work could be done as follows: firstly, in response to the limitation in this thesis, alternative data with better quality and broader time span should be explored. Furthermore, multiple types of data reflecting manifold sources of information, should be combined in risk analysis to reflect multi-perspectives of risks. Last but not least, the further work should be devoted to convert risk evaluations to effective regulatory tools to instruct risk supervision in practice. The future research questions could possibly be: the role of derivatives data (data from derivatives other than CDS) in risk analysis as compared with CDS data, equity data and accounting data.

Appendix

Appendix 1 List of Companies

Banks	Country	Insurers	Country	Non-FIs	Country
American Express	US	Aetna Inc.	US	3M	US
Bank of America	US	AIG	US	Altria Group	US
Capital One Financial	US	Allstate	US	Amgen Inc.	US
Citigroup Inc.	US	American Financial	US	AT&T Inc.	US
Goldman Sachs	US	Berkshire Hathaway	US	Cisco Systems	US
JPMorgan Chase&Co.	US	Chubb Limited	US	Coca-Cola	US
Morgan Stanley	US	Cigna Corporation	US	Eli Lilly and Co.	US
Wells Fargo & Co.	US	CNA Financial	US	Exxon Mobil	US
Banco Santander	Spain	The Hartford	US	The Home Depot	US
KBC Bank	Belgium	Lincoln National	US	Honeywell	US
BNP Paribas	France	Loews Corporation	US	Johnson & Johnson	US
Credit Agricole	France	Marsh & McLennan	US	McDonald's	US
Societe Generale	France	MBIA	US	Merck & Co.	US
Commerzbank AG	Germany	MetLife	US	PepsiCo, Inc.	US
Deutsche Bank	Germany	MGIC	US	Pfizer Inc.	US
Intesa Sanpaolo	Italy	Radian Group	US	Procter & Gamble	US
UniCredit	Italy	The Travelers Co.	US	Walmart	US
ING Group	Netherlands	Unum Group	US	Walt Disney	US
Nordea Bank	Sweden	AXA	France	LVMH	France
Credit Suisse Group	Switzerland	Scor SE	France	Sanofi S.A.	France
UBS AG	Switzerland	Allianz SE	Germany	Total S.A.	France
Barclays	UK	Hannover Re SE	Germany	BASF SE	Germany
HSBC Holdings	UK	Munich Re Group	Germany	Bayer AG	Germany
Lloyds Banking	UK	Assicurazioni Generali	Italy	BMW	Germany
RBS	UK	Aegon N.V.	Netherlands	Deutsche Telekom	Germany
Standard Chartered	UK	AON Plc	UK	Medtronic	Ireland
ANZ	Australia	Aviva Plc	UK	Nestle S.A.	Switzerland
Macquarie Group	Australia	Legal & General	UK	BP Plc	UK
National Australia	Australia	Old Mutual Plc	UK	AstraZeneca Plc	UK
ICICI Bank	India	Prudential Plc	UK	Vodafone Group	UK
KB Kookmin Bank	South Korea	QBE Insurance	Autralia	Japan Tobacco	Japan
Shinhan Bank	South Korea	Cathay Financial	Taiwan	Toyota Motor	Japan

Appendix 2 Descriptive Statistics of CDSs by Company

Company	Mean	St.dev.	Min	Max
3M	27.9526	22.01611	4.3	140
AIG	**281.5753**	**459.4588**	8	**3683.12**
AON Plc	60.67029	29.06967	23.3	159.42
AT&T Inc.	39.43228	16.26042	7.5	139.6
AXA	111.1887	86.46018	8.2	388.74
Aegon N.V.	137.4095	104.3087	8.2	625
Aetna Inc.	53.5905	29.34715	11.6	204
Allianz SE	62.36349	38.28839	5.5	192.45
Allstate	70.25606	61.99243	8.9	415.23
Altria Group	76.34063	35.33108	18.5	228.335
American Express	94.4358	107.6882	8	712
American Financial	120.5792	60.00617	20.8	179.45
Amgen Inc	44.63566	23.30166	5.3	130
Assicurazioni Ge	118.9811	106.1489	5.5	441.4099
AstraZeneca Plc	44.84363	32.67211	2.9	213.3
ANZ	78.09961	53.93927	4.4	239.45
Aviva Plc	102.3527	74.7933	5.5	515
BASF SE	58.42499	38.80003	8.3	176.4
BMW	82.41493	76.59013	8.1	518.6
BNP Paribas	83.27619	71.85257	5	361.1599
BP Plc	59.41531	64.31477	3	594.53
Banco Santander	133.943	117.4009	7	489.6
Bank of America	114.861	94.49577	7.8	487.5398
Barclays	95.16901	68.18481	5.3	282.6089
Bayer AG	52.46108	24.56132	14	154.95
Berkshire Hathaway	100.9266	85.66106	6.5	525
CNA Financial	133.0835	94.9419	27	463.3
Capital One	126.3647	106.12	21.4	570
Cathay Financial	85.71825	57.33019	13.5	350
Cigna	73.98725	55.03205	11.1	406.7
Cisco Systems	46.70067	30.38541	5.6	181
Citigroup	128.4471	111.5519	6.8	666.57
Coca-Cola	30.39089	16.65775	6.4	104.7
Commerzbank AG	101.59	77.32044	7.4	361.25
Credit Agricole	102.1247	84.73732	5.5	397.8899
Credit Suisse	80.14224	52.59022	9.2	262.88
Deutsche Bank	83.49124	54.44783	8.7	308.1399
Deutsche Telekom	72.69044	30.85568	20.7	193.3
Eli Lilly	34.1516	21.15843	4	81.28
Exxon Mobil	22.50868	17.58136	2.5	115
Goldman Sachs	124.3479	91.33809	16	620
HSBC Holdings	69.08947	45.31237	4.9	196.13
Hannover Re SE	68.27739	39.10878	7.5	156.423

Honeywell	33.58528	20.63307	10.5	155
ICICI Bank	244.409	166.1124	44	1794
ING Group	89.46746	63.05261	1	268.2798
Intesa Sanpaolo	134.3286	136.2714	5.4	607.8899
JPMorgan Chase & Co	73.5369	41.96957	11	242.05
Japan Tobacco	35.90476	24.55688	2	160
Johnson & Johnson	25.05484	16.73658	2.9	80.3
KB Kookmin Bank	115.2332	103.4344	12.1	830
KBC Bank	134.5522	108.7965	6.9	508.3999
LVMH	57.41444	29.40608	13.9	229.6
Legal & General	**122.0797**	**152.3319**	7.5	**1112.18**
Lincoln National	**198.0811**	**289.9147**	11	**3189.145**
Lloyds Banking	112.5624	94.56347	3.5	383.5
Loews Corporation	51.34251	28.75057	10.5	174.35
MBIA	**728.9861**	**569.7969**	18.7	**2425.17**
MGIC	**615.0838**	**547.5275**	23.5	**2228.83**
Macquarie Group	151.2694	136.7055	9.6	850
Marsh & McLennan	64.05191	27.47998	18.45	164.5
McDonald	28.64297	12.43452	8.5	79.9
Medtronic	47.24838	32.71351	6.4	180
Merck & Co.	52.05516	36.67131	10.7	215
MetLife	**161.9366**	**166.8902**	10.1	**1028.49**
Morgan Stanley	**157.3864**	**137.64**	17	**1300.9**
Munich Re Group	47.80157	24.21273	5	129.7
National Australia	78.45448	54.04505	4.5	239.95
Nestle S.A.	29.98614	18.81461	2.5	90
Nordea Bank	63.08064	45.26462	5	200.37
Old Mutual	**210.0561**	**350.5137**	11.3	**2866.03**
PepsiCo, Inc.	37.24975	19.95174	5.5	105
Pfizer Inc.	37.61121	26.05839	3	132
Procter & Gamble	38.36057	25.50839	5.4	157.8
Prudential Plc	111.1867	120.503	7	938.77
QBE Insurance	142.4281	104.5363	8.5	497.92
Radian Group	**846.0016**	**813.8016**	26.6	**3576.657**
RBS	124.4779	97.31428	3.5	406.7798
Sanofi S.A.	46.16595	24.04322	8	135.9
Scor SE	87.81006	54.98085	10.8	253.07
Shinhan Bank	122.3198	111.684	14	630
Societe Generale	106.8797	92.98141	5.7	434.6299
Standard Charter	86.6674	61.14728	5.5	352.06
The Hartford	**169.3279**	**186.3322**	9.9	**1151.88**
The Home Depot	60.39647	58.05714	7.3	360
The Travelers Co.	62.88551	34.26668	14.5	178.99
Total S.A.	42.63964	28.39009	5.2	160
Toyota Motor	47.06249	45.53735	1.5	290
UBS AG	86.40476	67.62681	4	360

UniCredit	152.5482	145.5418	7	678.3098
Unum Group	171.2337	82.57939	45	423.69
Vodafone Group	69.08665	35.45083	18.7	225.7
Walmart	34.09324	22.44155	4.9	130
Walt Disney	34.3585	18.25152	7.7	135
Wells Fargo & Co	71.43657	50.67934	6	312.5
Chubb Limited	47.34919	27.93914	8.6	191.7

The table presents mean values, standard deviations, minimum values and maximum values of CDS spread for each of the 96 companies. Sample period is from 3rd January 2005 to 31st December 2014, thus observation number is 2608 for all companies. Firms with maximum CDS values exceeding 1000 are in bold.

Appendix 3 Descriptive Statistics of CDS by Industry

Sector	Mean	St.Dev.	Min	Max
Banks	110.0124	101.3214	1	1794
Insurers	169.3313	309.0164	5	3683.12
NFIs	45.28999	36.07558	1.5	594.53

The table presents mean values, standard deviations, minimum values and maximum values of CDS spread for each of the 3 sectors. Observation number is 83456 (32×2608) for all sectors.

Appendix 4 Descriptive Statistics of Equity Returns by Company

Company	Mean	St.Dev.	Min	Max
3M	0.0002648	0.0139535	-0.0938369	0.0942038
AIG	**-0.0011444**	**0.0490621**	**-0.9362577**	0.5068166
AON Plc	0.0005338	0.01567	-0.1484011	0.1561607
AT&T Inc.	0.0001043	0.0138197	-0.0803551	0.1508318
AXA	0.0000327	0.0265372	-0.2035017	0.1977824
Aegon N.V.	-0.0001509	0.029618	-0.2768359	0.3021541
Aetna Inc.	0.0004076	0.02245	-0.2270279	0.1634188
Allianz SE	0.0001336	0.020406	-0.1391798	0.1780799
Allstate	0.0001212	0.0217465	-0.2379861	0.1962799
Altria Group	0.0004817	0.0122027	-0.132666	0.1516501
American Express	0.0002464	0.0242289	-0.1935233	0.1877116
American Financial	0.000413	0.0208203	-0.1552624	0.3741066
Amgen	0.0003481	0.0165473	-0.0989767	0.1406494
Assicurazioni	-0.0000983	0.0169941	-0.0923087	0.1231283
AstraZeneca	0.0003377	0.0145555	-0.117796	0.1343123
ANZ	0.0001702	0.016739	-0.1157429	0.1365204
Aviva	**-0.0000995**	**0.0268576**	**-0.4059916**	0.2239155
BASF SE	0.0003714	0.0177643	-0.1292391	0.1269062
BMW	0.0003765	0.019824	-0.1305267	0.1351835
BNP Paribas	-0.0000192	0.0260843	-0.1892621	0.1897678
BP Plc	-0.0000813	0.0164144	-0.1403684	0.1058255
Banco Santander	0.0000641	0.0215954	-0.1271623	0.2087859
Bank of America	-0.0003661	0.0356493	-0.3420588	0.3020961
Barclays	-0.0002963	0.0332615	-0.2856365	0.549477
Bayer AG	0.0006019	0.0171985	-0.1049652	0.108023
Berkshire Hathaway	0.0003657	0.0141169	-0.1288329	0.1495317
CNA Financial	**0.0001481**	**0.0257438**	**-0.3947638**	0.2410588
Capital One	-5.76E-06	0.0315604	-0.2882425	0.2345196
Cathay Financial	9.26E-06	0.0196924	-0.0726031	0.0677208
Cigna Corporation	0.000518	0.0242317	-0.242216	0.2113947
Cisco Systems	0.0001398	0.0189595	-0.1768648	0.147993
Citigroup	**-0.0008394**	**0.0376085**	**-0.4946962**	0.4563162
Coca-Cola	0.0002721	0.011392	-0.0906805	0.1299708
Commerzbank AG	-0.000815	0.0310769	-0.2824824	0.1945733
Credit Agricole	-0.0002433	0.0283162	-0.1434817	0.2336148
Credit Suisse	-0.000242	0.0244639	-0.1766572	0.246122
Deutsche Bank	-0.0003141	0.0252928	-0.1807454	0.2230318
Deutsche Telekom	-0.0000867	0.0150717	-0.1325544	0.1325544
Eli Lilly and Co.	0.0000783	0.0138758	-0.131799	0.1340893
Exxon Mobil	0.0002351	0.0157019	-0.150271	0.1586307
Goldman Sachs	0.0002353	0.0246129	-0.2102226	0.2348178
HSBC Holdings	-0.0000882	0.0174087	-0.2079934	0.1442285

Hannover Re SE	0.0003633	0.0197347	-0.1536385	0.1331667
Honeywell	0.0003991	0.0169503	-0.098805	0.1110663
ICICI Bank	0.000598	0.0268907	-0.2213545	0.2073239
ING Group	-0.0001792	0.032172	-0.3213612	0.2565265
Intesa Sanpaolo	-0.000116	0.0263951	-0.1846294	0.1796358
JPMorgan Chase & Co.	0.0001799	0.0267511	-0.232278	0.2239172
Japan Tobacco	0.000401	0.0210703	-0.1324031	0.1324031
Johnson & Johnson	0.000195	0.0099315	-0.0797488	0.1153729
KB Kookmin Bank	-0.0000446	0.0239389	-0.1613979	0.1397621
KBC Bank	-0.0000731	0.0361036	-0.2866355	0.4048425
LVMH	0.0003654	0.0177622	-0.1193052	0.1213783
Legal & General	0.0003128	0.0258808	-0.3407595	0.2430024
Lincoln National	**0.0000858**	**0.0403995**	**-0.5089086**	0.3623487
Lloyds Banking Group	**-0.0004333**	**0.0341992**	**-0.4147273**	0.4077654
Loews Corporation	0.0002287	0.0195626	-0.199394	0.2122027
MBIA	**-0.0007233**	**0.049261**	**-0.4126444**	0.3821945
MGIC	**-0.0007599**	**0.0620362**	**-1.023808**	0.5575128
Macquarie Group	0.0000931	0.0253986	-0.2642844	0.3207205
Marsh & McLennan	0.0002124	0.0160982	-0.1307455	0.1348
McDonald	0.0004143	0.0122291	-0.0831566	0.0897446
Medtronic	0.0001453	0.0149559	-0.1419609	0.0980337
Merck & Co.	0.000229	0.016583	-0.1594444	0.122509
MetLife	0.0001142	0.0304752	-0.3115613	0.2468601
Morgan Stanley	-0.0000686	0.0351127	-0.2996583	0.62585
Munich Re Group	0.0002309	0.0157934	-0.1114155	0.1450963
National Australia	0.0000589	0.0170442	-0.1448567	0.1599668
Nestle S.A.	0.0003396	0.010963	-0.0690267	0.0904182
Nordea Bank	0.0002078	0.0208392	-0.1203243	0.1490748
Old Mutual Plc	0.0001376	0.0269532	-0.2438824	0.2643066
PepsiCo, Inc.	0.0002298	0.0107088	-0.1270537	0.0820445
Pfizer Inc.	0.0000627	0.0145059	-0.1123242	0.0968701
Procter & Gamble	0.0001922	0.0109392	-0.082264	0.0972574
Prudential Plc	0.0004572	0.0268805	-0.2231435	0.210721
QBE Insurance	-0.0001206	0.0190791	-0.2527024	0.1041962
Radian Group	-0.0004372	0.0602574	-0.3667862	0.6048965
RBS	**-0.0009657**	**0.0403829**	**-1.095735**	0.3050463
Sanofi S.A.	0.0000935	0.0157101	-0.1124466	0.1368112
Scor SE	0.000239	0.0182978	-0.1017557	0.1354843
Shinhan Bank	0.0002605	0.0218067	-0.1620014	0.134995
Societe Generale	-0.0002424	0.0291966	-0.1771218	0.2142546
Standard Chartered	0.0000632	0.0245842	-0.1794696	0.2623711
The Hartford	**-0.0001922**	**0.0441063**	**-0.7248634**	0.7048674
The Home Depot	0.0003414	0.0170065	-0.0857927	0.1316126
The Travelers Co.	0.0004006	0.018406	-0.2006707	0.2275781
Total S.A.	0.000027	0.0160391	-0.0964049	0.1278599
Toyota Motor	0.0002281	0.0185724	-0.1231885	0.1443423

UBS AG	-0.0002566	0.025964	-0.1736276	0.2589268
UniCredit	-0.0005632	0.0294287	-0.1895475	0.1900674
Unum Group	0.0002641	0.0265327	-0.351448	0.2000952
Vodafone Group	0.0001655	0.0163876	-0.1458503	0.0907243
Walmart	0.0001826	0.0117572	-0.0840767	0.1050182
Walt Disney	0.0004725	0.0170174	-0.1023062	0.1481805
Wells Fargo & Co	0.0002192	0.0289886	-0.272101	0.2834067
Chubb Limited	0.000383	0.0187972	-0.2201229	0.1885788
Total	0.0000681	0.0253978	-1.095735	0.7048674

The table presents mean values, standard deviations, minimum values and maximum values of equity returns for each of the 96 companies. Sample period is from 3rd January 2005 to 31st December 2014, thus there are 2608 equity values. After convert stock price to equity returns, observation number becomes 2607 for all companies. Firms with minimum equity returns lower than -0.39 are in bold.

Appendix 5 Descriptive Statistics of Equity Returns by Industry

Sector	Mean	St.Dev.	Min	Max
Banks	-0.000118	0.0282143	-1.095735	0.62585
Insurers	0.0000746	0.0300046	-1.023808	0.7048674
NFIs	0.0002477	0.0154522	-0.1768648	0.1586307
Total	0.0000681	0.0253978	-1.095735	0.7048674

The table presents mean values, standard deviations, minimum values and maximum values of equity returns for each of the 3 sectors. Observation number is 83424 (32×2607) for all sectors.

Appendix 6 Descriptive Statistics of EA

Sector	Mean	St.Dev.	Min	Max
Banks	0.0623622	0.0324624	0.0073446	0.1826757
Insurers	0.1470079	0.1196682	0.012816	0.6626226
NFIs	0.4408854	0.1159747	0.0718646	0.7935777
Total	0.2167518	0.1895312	0.0073446	0.7935777

The table presents mean values, standard deviations, minimum values and maximum values of equity over assets (EA) for each of the 3 sectors. Sample period ranges from 2005 Q1 to 2014 Q4, thus there are 40 observations for each company and 1280 (32×40) observations for each sector.

Appendix 7 Descriptive Statistics of ROA

Sector	Mean	St.Dev.	Min	Max
Banks	0.0024588	0.0226234	-0.0161414	0.8070404
Insurers	0.0032003	0.0121277	-0.1900672	0.0695376
NFIs	0.0227773	0.0184358	-0.1950347	0.1433293
Total	0.0094788	0.0205254	-0.1950347	0.8070404

The table presents mean values, standard deviations, minimum values and maximum values of return on assets (ROA) for each of the 3 sectors. Observation number is 1280 (32×40) for all sectors.

Appendix 8 Results of One-Sample Wilcoxon Signed-Rank Test on the Firm-Level Risk Measures

Company	Volatility	VaR	ES	Beta	CDS	Z-Score
American Express	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Bank of America	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Capital One Financial	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Citigroup Inc.	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Goldman Sachs	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
JPMorgan Chase&Co.	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Morgan Stanley	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Wells Fargo & Co.	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Banco Santander	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
KBC Bank	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
BNP Paribas	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Credit Agricole	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Societe Generale	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Commerzbank AG	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Deutsche Bank	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Intesa Sanpaolo	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
UniCredit	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
ING Group	0.000***	0.000***	0.000***	0.000***	0.000***	0.001***
Nordea Bank	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Credit Suisse Group	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
UBS AG	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Barclays	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
HSBC Holdings	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Lloyds Banking	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
RBS	0.000***	0.000***	0.000***	0.000***	0.000***	0.001***
Standard Chartered	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
ANZ	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Macquarie Group	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
National Australia	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
ICICI Bank	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
KB Kookmin Bank	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Shinhan Bank	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Aetna Inc.	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
AIG	0.000***	0.000***	0.000***	0.000***	0.000***	0.004***
Allstate	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
American Financial	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Berkshire Hathaway	0.000***	0.000***	0.000***	0.000***	0.000***	0.002***
Chubb Limited	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Cigna Corporation	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
CNA Financial	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
The Hartford	0.000***	0.000***	0.000***	0.000***	0.000***	0.001***
Lincoln National	0.000***	0.000***	0.000***	0.000***	0.000***	0.003***
Loews Corporation	0.000***	0.000***	0.000***	0.000***	0.000***	0.95712

Marsh & McLennan	0.000***	0.000***	0.000***	0.000***	0.000***	0.96783
MBIA	0.000***	0.000***	0.000***	0.000***	0.000***	0.17037
MetLife	0.000***	0.000***	0.000***	0.000***	0.000***	0.17891
MGIC	0.000***	0.000***	0.000***	0.000***	0.000***	0.71667
Radian Group	0.000***	0.000***	0.000***	0.000***	0.000***	0.030**
The Travelers Co.	0.000***	0.000***	0.000***	0.000***	0.000***	0.17891
Unum Group	0.000***	0.000***	0.000***	0.000***	0.000***	0.002***
AXA	0.000***	0.000***	0.000***	0.000***	0.000***	0.066*
Scor SE	0.000***	0.000***	0.000***	0.000***	0.000***	0.16214
Allianz SE	0.000***	0.000***	0.000***	0.000***	0.000***	0.21624
Hannover Re SE	0.000***	0.000***	0.000***	0.000***	0.000***	0.055*
Munich Re Group	0.000***	0.000***	0.000***	0.000***	0.000***	0.95712
Assicurazioni Generali	0.000***	0.000***	0.000***	0.000***	0.000***	0.011**
Aegon N.V.	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
AON Plc	0.000***	0.000***	0.000***	0.000***	0.000***	0.45974
Aviva Plc	0.000***	0.000***	0.000***	0.000***	0.000***	0.87186
Legal & General	0.000***	0.000***	0.000***	0.000***	0.000***	0.001***
Old Mutual Plc	0.000***	0.000***	0.000***	0.000***	0.000***	0.008***
Prudential Plc	0.000***	0.000***	0.000***	0.000***	0.000***	0.023**
QBE Insurance	0.000***	0.000***	0.000***	0.000***	0.000***	0.002***
Cathay Financial	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
3M	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Altria Group	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Amgen Inc.	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
AT&T Inc.	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Cisco Systems	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Coca-Cola	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Eli Lilly and Co.	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Exxon Mobil	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
The Home Depot	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Honeywell	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Johnson & Johnson	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
McDonald's	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Merck & Co.	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
PepsiCo, Inc.	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Pfizer Inc.	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Procter & Gamble	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Walmart	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Walt Disney	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
LVMH	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Sanofi S.A.	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Total S.A.	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
BASF SE	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Bayer AG	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
BMW	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Deutsche Telekom	0.000***	0.000***	0.000***	0.000***	0.000***	0.016**

Medtronic	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Nestle S.A.	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
BP Plc	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
AstraZeneca Plc	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Vodafone Group	0.000***	0.000***	0.000***	0.000***	0.000***	0.86129
Japan Tobacco	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Toyota Motor	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***

Appendix 9 Results of Kruskal-Wallis Test on the Firm-Level Risk Measures

Banks		Insurers		NFIs	
American Express	0.000***	Aetna Inc.	0.000***	3M	0.000***
Bank of America	0.000***	AIG	0.000***	Altria Group	0.000***
Capital One Financial	0.000***	Allstate	0.000***	Amgen Inc.	0.000***
Citigroup Inc.	0.000***	American Financial	0.000***	AT&T Inc.	0.000***
Goldman Sachs	0.000***	Berkshire Hathaway	0.000***	Cisco Systems	0.000***
JPMorgan Chase&Co.	0.000***	Chubb Limited	0.000***	Coca-Cola	0.000***
Morgan Stanley	0.000***	Cigna Corporation	0.000***	Eli Lilly and Co.	0.000***
Wells Fargo & Co.	0.000***	CNA Financial	0.000***	Exxon Mobil	0.000***
Banco Santander	0.000***	The Hartford	0.000***	The Home Depot	0.000***
KBC Bank	0.000***	Lincoln National	0.000***	Honeywell	0.000***
BNP Paribas	0.000***	Loews Corporation	0.000***	Johnson & Johnson	0.000***
Credit Agricole	0.000***	Marsh & McLennan	0.000***	McDonald's	0.000***
Societe Generale	0.000***	MBIA	0.000***	Merck & Co.	0.000***
Commerzbank AG	0.000***	MetLife	0.000***	PepsiCo, Inc.	0.000***
Deutsche Bank	0.000***	MGIC	0.000***	Pfizer Inc.	0.000***
Intesa Sanpaolo	0.000***	Radian Group	0.000***	Procter & Gamble	0.000***
UniCredit	0.000***	The Travelers Co.	0.000***	Walmart	0.000***
ING Group	0.000***	Unum Group	0.000***	Walt Disney	0.000***
Nordea Bank	0.000***	AXA	0.000***	LVMH	0.000***
Credit Suisse Group	0.000***	Scor SE	0.000***	Sanofi S.A.	0.000***
UBS AG	0.000***	Allianz SE	0.000***	Total S.A.	0.000***
Barclays	0.000***	Hannover Re SE	0.000***	BASF SE	0.000***
HSBC Holdings	0.000***	Munich Re Group	0.000***	Bayer AG	0.000***
Lloyds Banking	0.000***	Assicurazioni Generali	0.000***	BMW	0.000***
RBS	0.000***	Aegon N.V.	0.000***	Deutsche Telekom	0.000***
Standard Chartered	0.000***	AON Plc	0.000***	Medtronic	0.000***
ANZ	0.000***	Aviva Plc	0.000***	Nestle S.A.	0.000***
Macquarie Group	0.000***	Legal & General	0.000***	BP Plc	0.000***
National Australia	0.000***	Old Mutual Plc	0.000***	AstraZeneca Plc	0.000***
ICICI Bank	0.000***	Prudential Plc	0.000***	Vodafone Group	0.000***
KB Kookmin Bank	0.000***	QBE Insurance	0.000***	Japan Tobacco	0.000***
Shinhan Bank	0.000***	Cathay Financial	0.000***	Toyota Motor	0.000***

Appendix 10 Results of Conover-Iman Test on Volatility for Sector Risk Ranking

Volatility (Pre-crisis)	Volatility (Crisis)	Volatility (Post-crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 4.4465, df = 2, p-value = 0.11	data: x and g Kruskal-Wallis chi-squared = 9.015, df = 2, p-value = 0.01	data: x and g Kruskal-Wallis chi-squared = 26.7291, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs t statistic (adjusted p-value)	Pairs t statistic (adjusted p-value)	Pairs t statistic (adjusted p-value)
Insurers - Banks : 1.145321 (0.7208)	Insurers - Banks : 0.129973 (1.0000)	Insurers - Banks : -1.360283 (0.3274)
Insurers - NFIs : 2.210736 (0.1964)	Insurers - NFIs : 3.249336 (0.0211)**	Insurers - NFIs : 4.942361 (0.0000)***
Banks - NFIs : 1.065415 (0.5429)	Banks - NFIs : 3.119362 (0.0143)**	Banks - NFIs : 6.302645 (0.0000)***

Appendix 11 Results of Conover-Iman Test on VaR for Sector Risk Ranking

VaR(Pre-crisis)	VaR(Crisis)	VaR(Post-Crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 1.7729, df = 2, p-value = 0.41	data: x and g Kruskal-Wallis chi-squared = 8.765, df = 2, p-value = 0.01	data: x and g Kruskal-Wallis chi-squared = 25.7565, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs t statistic (adjusted p-value)	Pairs t statistic (adjusted p-value)	Pairs t statistic (adjusted p-value)
Insurers - Banks : 0.379408 (1.0000)	Insurers - Banks : 0.429423 (1.0000)	Insurers - Banks : -1.810976 (0.1373)
Insurers - NFIs : 1.289987 (1.0000)	Insurers - NFIs : 3.306561 (0.0185)**	Insurers - NFIs : 4.437886 (0.0001)***
Banks - NFIs : 0.910579 (1.0000)	Banks - NFIs : 2.877138 (0.0248)**	Banks - NFIs : 6.248863 (0.0000)***

Appendix 12 Results of Conover-Iman Test on ES for Sector Risk Ranking

ES(Pre-crisis)	ES(Crisis)	ES(Post-Crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 1.489, df = 2, p-value = 0.47	data: x and g Kruskal-Wallis chi-squared = 8.495, df = 2, p-value = 0.01	data: x and g Kruskal-Wallis chi-squared = 26.1263, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs t statistic (adjusted p-value)	Pairs t statistic (adjusted p-value)	Pairs t statistic (adjusted p-value)
Insurers - Banks : 0.880706 (1.0000)	Insurers - Banks : 0.553030 (1.0000)	Insurers - Banks : -1.229709 (0.4095)
Insurers - NFIs : 1.157499 (1.0000)	Insurers - NFIs : 3.275642 (0.0199)**	Insurers - NFIs : 4.918836 (0.0000)***
Banks - NFIs : 0.276793 (1.0000)	Banks - NFIs : 2.722612 (0.0351)**	Banks - NFIs : 6.148545 (0.0000)***

Appendix 13 Results of Conover-Iman Test on Beta for Sector Risk Ranking

Beta(Pre-crisis)	Beta(Crisis)	Beta(Post-Crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 17.9381, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 15.965, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 44.6942, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs t statistic (adjusted p-value)	Pairs t statistic (adjusted p-value)	Pairs t statistic (adjusted p-value)
Insurers - Banks : -1.428574 (0.3018)	Insurers - Banks : -1.343863 (0.3544)	Insurers - Banks : -2.932588 (0.0086)***
Insurers - NFIs : 4.880963 (0.0001)***	Insurers - NFIs : 5.192201 (0.0001)***	Insurers - NFIs : 8.410443 (0.0000)***
Banks - NFIs : 6.309538 (0.0000)***	Banks - NFIs : 6.536065 (0.0000)***	Banks - NFIs : 11.34303 (0.0000)***

Appendix 14 Results of Conover-Iman Test on CDS Spread for Sector Risk Ranking

CDS(Pre-crisis)	CDS(Crisis)	CDS(Post-Crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 13.9845, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 8.705, df = 2, p-value = 0.01	data: x and g Kruskal-Wallis chi-squared = 45.4504, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs t statistic (adjusted p-value)	Pairs t statistic (adjusted p-value)	Pairs t statistic (adjusted p-value)
Insurers - Banks : 4.325637 (0.0005)***	Insurers - Banks : 1.456972 (0.2932)	Insurers - Banks : 2.918273 (0.0089)***
Insurers - NFIs : 4.359697 (0.0009)***	Insurers - NFIs : 3.556728 (0.0103)**	Insurers - NFIs : 11.63080 (0.0000)***
Banks - NFIs : 0.034060 (1.0000)	Banks - NFIs : 2.099755 (0.1320)	Banks - NFIs : 8.712528 (0.0000)***

Appendix 15 Results of Conover-Iman Test on Z-Score for Sector Risk Ranking

Zscore(Pre-crisis)	Zscore(Crisis)	Zscore(Post-Crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 19.2723, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 18.005, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 47.6418, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs t statistic (adjusted p-value)	Pairs t statistic (adjusted p-value)	Pairs t statistic (adjusted p-value)
Insurers - Banks : -4.739450 (0.0002)***	Insurers - Banks : -5.291999 (0.0001)***	Insurers - Banks : -8.887081 (0.0000)***
Insurers - NFIs : -7.193809 (0.0000)***	Insurers - NFIs : -8.626683 (0.0000)***	Insurers - NFIs : -12.83689 (0.0000)***
Banks - NFIs : -2.454358 (0.0382)**	Banks - NFIs : -3.334684 (0.0058)***	Banks - NFIs : -3.949814 (0.0004)***

Appendix 16 Results of Conover-Iman Test on Volatility for Time Period Risk Ranking

Volatility (banks)	Volatility (insurers)	Volatility(NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g	data: x and g	data: x and g
Kruskal-Wallis chi-squared = 24.1775, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 20.9514, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 16.3392, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : 3.552430 (0.0019)***	Crisis - Post-crisis : 4.062069 (0.0007)***	Crisis - Post-crisis : 4.533757(0.0002)***
Crisis - Pre-crisis : 7.585906 (0.0000)***	Crisis - Pre-crisis : 6.551821 (0.0000)***	Crisis - Pre-crisis : 4.798723 (0.0001)***
Post-crisis - Pre-crisis : 5.589234 (0.0000)***	Post-crisis - Pre-crisis : 3.751406 (0.0011)***	Post-crisis - Pre-crisis : 1.060400 (0.5424)

Appendix 17 Results of Conover-Iman Test on VaR for Time Period Risk Ranking

VaR (banks)	VaR (insurers)	VaR(NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g	data: x and g	data: x and g
Kruskal-Wallis chi-squared = 23.8919, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 21.3571, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 15.5367, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pair: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : 3.868717 (0.0008)***	Crisis - Post-crisis : 4.210802 (0.0004)***	Crisis - Post-crisis : 4.242678 (0.0004)***
Crisis - Pre-crisis : 7.549136 (0.0000)***	Crisis - Pre-crisis : 6.692023 (0.0000)***	Crisis - Pre-crisis : 4.670656 (0.0002)***
Post-crisis - Pre-crisis : 5.201109 (0.0000)***	Post-crisis - Pre-crisis : 3.764772 (0.0011)***	Post-crisis - Pre-crisis : 1.216221 (0.4246)

Appendix 18 Results of Conover-Iman Test on ES for Time Period Risk Ranking

ES (banks)	ES (insurers)	ES(NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g	data: x and g	data: x and g
Kruskal-Wallis chi-squared = 23.1156, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 22.5834, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 17.1422, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : 3.693939 (0.0013)***	Crisis - Post-crisis : 4.199113 (0.0003)***	Crisis - Post-crisis : 4.469252 (0.0002)***
Crisis - Pre-crisis : 7.238493 (0.0000)***	Crisis - Pre-crisis : 7.120207 (0.0000)***	Crisis - Pre-crisis : 5.167627 (0.0000)***
Post-crisis - Pre-crisis : 5.003954 (0.0000)***	Post-crisis - Pre-crisis : 4.309972 (0.0003)***	Post-crisis - Pre-crisis : 1.589048 (0.2210)

Appendix 19 Results of Conover-Iman Test on Beta for Time Period Risk Ranking

Beta (banks)	Beta (insurers)	Beta (NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g	data: x and g	data: x and g
Kruskal-Wallis chi-squared = 18.7796, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 16.8847, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 11.6909, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : 0.780322 (0.8070)	Crisis - Post-crisis : 1.227272 (0.4170)	Crisis - Post-crisis : -2.156767 (0.0689)
Crisis - Pre-crisis : 4.970517 (0.0000)***	Crisis - Pre-crisis : 4.764239 (0.0002)***	Crisis - Pre-crisis : -3.951476 (0.0018)***
Post-crisis - Pre-crisis : 5.337278 (0.0000)***	Post-crisis - Pre-crisis : 4.596886 (0.0001)***	Post-crisis - Pre-crisis : -2.579816 (0.0385)**

Appendix 20 Results of Conover-Iman Test on CDS Spread for Time Period Risk Ranking

CDS (banks)	CDS (insurers)	CDS(NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g	data: x and g	data: x and g
Kruskal-Wallis chi-squared = 21.9712, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 22.0522, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 22.2705, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : -0.208229 (1.0000)	Crisis - Post-crisis : 0.469634 (1.0000)	Crisis - Post-crisis : 0.840335 (0.7446)
Crisis - Pre-crisis : 5.183469 (0.0000)***	Crisis - Pre-crisis : 5.628840 (0.0000)***	Crisis - Pre-crisis : 5.900103 (0.0000)***
Post-crisis - Pre-crisis : 6.672273 (0.0000)***	Post-crisis - Pre-crisis : 6.492387 (0.0000)***	Post-crisis - Pre-crisis : 6.428471 (0.0000)***

Appendix 21 Results of Conover-Iman Test on Z-Score for Time Period Risk Ranking

Z-Score (banks)	Z-Score (insurers)	Z-Score(NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g	data: x and g	data: x and g
Kruskal-Wallis chi-squared = 18.6837, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 3.3998, df = 2, p-value = 0.18	Kruskal-Wallis chi-squared = 8.5706, df = 2, p-value = 0.01
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pair: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : -5.789074 (0.0000)***	Crisis - Post-crisis : 0.062406 (1.0000)	Crisis - Post-crisis : -2.772725 (0.0238)**
Crisis - Pre-crisis : -4.246703 (0.0004)***	Crisis - Pre-crisis : -1.406415 (0.4618)	Crisis - Pre-crisis : -3.042444 (0.0236)**
Post-crisis - Pre-crisis : 0.985086 (0.6068)	Post-crisis - Pre-crisis : -1.816764 (0.4255)	Post-crisis - Pre-crisis : -0.782429 (0.8047)

Appendix 22 Rank Correlations between the Firm-Level Risk Measures Based on Time Series Data

Time series		Volatility	VaR	ES	Beta	CDS	Z-Score
Volatility	Spearman's ρ	1.000					
	P value	1.000					
VaR	Spearman's ρ	0.974	1.000				
	P value	0.000***	1.000				
ES	Spearman's ρ	0.982	0.987	1.000			
	P value	0.000***	0.000***	1.000			
Beta	Spearman's ρ	0.759	0.681	0.726	1.000		
	P value	0.000***	0.000***	0.000***	1.000		
CDS	Spearman's ρ	0.776	0.736	0.756	0.879	1.000	
	P value	0.000***	0.000***	0.000***	0.000***	1.000	
Z-Score	Spearman's ρ	-0.608	-0.583	-0.607	-0.491	-0.453	1.000
	P value	0.000***	0.000***	0.000***	0.001***	0.004***	1.000

Appendix 23 Rank Correlations between the Firm-Level Risk Measures Based on Cross-sectional data

Cross section		Volatility	VaR	ES	Beta	CDS	Z-Score
Volatility	Spearman's ρ	1.000					
	P value	1.000					
VaR	Spearman's ρ	0.993	1.000				
	P value	0.000***					
ES	Spearman's ρ	0.989	0.987	1.000			
	P value	0.000***	0.000***				
Beta	Spearman's ρ	0.855	0.865	0.846	1.000		
	P value	0.000***	0.000***	0.000***			
CDS	Spearman's ρ	0.819	0.823	0.820	0.661	1.000	
	P value	0.000***	0.000***	0.000***	0.000***		
Z-Score	Spearman's ρ	-0.342	-0.343	-0.366	-0.371	-0.401	1.000
	P value	0.001***	0.001***	0.000***	0.000***	0.000***	1.000

Appendix 24 Rank Correlations across Time by Firm-Level Risk Measures

		Volatility			VaR			ES		
		pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis
pre-crisis	Spearman's ρ	1.000			1.000			1.000		
	P value	1.000			1.000			1.000		
crisis	Spearman's ρ	0.223	1.000		0.276	1.000		0.221	1.000	
	P value	0.029**	1.000		0.007***	1.000		0.031**	1.000	
post-crisis	Spearman's ρ	0.352	0.799	1.000	0.368	0.809	1.000	0.340	0.775	1.000
	P value	0.000***	0.000***	1.000	0.000***	0.000***	1.000	0.001***	0.000***	1.000

(Continued)

		Beta			CDS			Z-Score		
		pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis
pre-crisis	Spearman's ρ	1.000			1.000			1.000		
	P value	1.000			1.000			1.000		
crisis	Spearman's ρ	0.592	1.000		0.477	1.000		0.681	1.000	
	P value	0.000***	1.000		0.000***	1.000		0.000***	1.000	
post-crisis	Spearman's ρ	0.679	0.855	1.000	0.238	0.755	1.000	0.596	0.651	1.000
	P value	0.000***	0.000***	1.000	0.020**	0.000***	1.000	0.000***	0.000***	1.000

Appendix 25 Company Risk Ranking Resulted from Volatility

2007 Q3	2007 Q4	2008 Q1	2008 Q2	2008 Q3	2008 Q4	2009 Q1	2009 Q2
Radian group	Radian group	MBIA	MBIA	Radian group	The Hartford	Citigroup Inc.	MGIC
MGIC	MBIA	Radian group	Radian group	AIG	Lincoln National	MGIC	Radian group
MBIA	MGIC	MGIC	MGIC	MGIC	MGIC	RBS	Capital One
Macquarie Group	Capital One	Macquarie Group	Macquarie Group	MBIA	Radian group	Lloyds Banking Group	The Hartford
Cathay Financial	Morgan Stanley	ICICI Bank	RBS	Bank of America	Morgan Stanley	Lincoln National	Lincoln National
Old Mutual Plc	ICICI Bank	Capital One	UBS AG	Capital One	MBIA	Bank of America	KBC Bank
Prudential Plc	RBS	CNA Financial	AIG	Morgan Stanley	Citigroup Inc.	The Hartford	AIG
Standard Chartered	Goldman Sachs	UBS AG	Capital One Financial	Citigroup Inc.	MetLife	AIG	Bank of America
Legal & General	Barclays	Morgan Stanley	Morgan Stanley	JPMorgan Chase & Co.	AIG	Barclays	MBIA
Morgan Stanley	Citigroup Inc.	RBS	Citigroup Inc.	UBS AG	Unum Group	Radian group	Wells Fargo & Co.
Barclays	Shinhan Bank	Citigroup Inc.	Commerzbank AG	Macquarie Group	CNA Financial	MBIA	Lloyds Banking
American Express	AIG	Societe Generale	Credit Agricole	Wells Fargo & Co.	ING Group	Wells Fargo & Co.	RBS
Capital One	Prudential Plc	Old Mutual Plc	Barclays	RBS	Aegon N.V.	KBC Bank	American Express
Goldman Sachs	Wells Fargo & Co.	Commerzbank AG	ICICI Bank	Old Mutual Plc	RBS	MetLife	CNA Financial
American Financial	KB Kookmin Bank	Barclays	National Australia	Barclays	Cigna Corporation	Capital One Financial	MetLife
Lincoln National	American Express	Wells Fargo & Co.	CNA Financial	Lloyds Banking Group	Bank of America	Aegon N.V.	Aegon N.V.
MetLife	Old Mutual Plc	QBE Insurance	American Express	ICICI Bank	Allstate	Legal & General	Citigroup Inc.
Unum Group	Unum Group	JPMorgan Chase & Co.	ANZ	Credit Agricole	Old Mutual Plc	ING Group	Barclays
ICICI Bank	Standard Chartered	American Express	JPMorgan Chase & Co.	Prudential Plc	Prudential Plc	Morgan Stanley	ICICI Bank
Commerzbank AG	Lincoln National	Credit Suisse	Lloyds Banking Group	Commerzbank AG	KBC Bank	Aviva Plc	ING Group

Appendix 26 Company Risk Ranking Resulted from VaR

2007 Q3	2007 Q4	2008 Q1	2008 Q2	2008 Q3	2008 Q4	2009 Q1	2009 Q2
Radian Group	MBIA	MBIA	Radian group	AIG	The Hartford	Lloyds Banking Group	KBC Bank
MGIC	Radian group	MGIC	MBIA	Radian group	MGIC	MGIC	MGIC
Macquarie Group	MGIC	Radian group	MGIC	MGIC	Morgan Stanley	KBC Bank	The Hartford
MBIA	Morgan Stanley	Macquarie Group	Macquarie Group	MBIA	Radian group	Citigroup Inc.	Radian group
Prudential Plc	Citigroup Inc.	Societe Generale	AIG	UBS AG	Citigroup Inc.	AIG	Capital One
Old Mutual Plc	Barclays	UBS AG	Citigroup Inc.	Morgan Stanley	Lincoln National	Lincoln National	AIG
Cathay Financial	RBS	Credit Suisse Group	RBS	JPMorgan Chase & Co.	MBIA	The Hartford	Lincoln National
The Home Depot	Capital One	ICICI Bank	Barclays	RBS	AIG	Bank of America	MBIA
Lincoln National	Wells Fargo & Co.	QBE Insurance Group	Credit Agricole	Citigroup Inc.	RBS	Barclays	Bank of America
Barclays	Shinhan Bank	Citigroup Inc.	UBS AG	Old Mutual Plc	MetLife	Capital One	Lloyds Banking Group
Commerzbank AG	Goldman Sachs	Commerzbank AG	Legal & General	Bank of America	KB Kookmin Bank	MetLife	MetLife
MetLife	AIG	Old Mutual Plc	Wells Fargo & Co.	ICICI Bank	CNA Financial	Radian group	Barclays
Marsh & McLennan	American Express	RBS	Capital One Financial	Commerzbank AG	Loews Corporation	MBIA	CNA Financial
Capital One	Prudential Plc	National Australia	Japan Tobacco Inc.	Macquarie Group	Aegon N.V.	Wells Fargo & Co.	Legal & General
Goldman Sachs	Lincoln National	KBC Bank	Commerzbank AG	The Hartford	KBC Bank	RBS	Wells Fargo
CNA Financial	KB Kookmin Bank	ANZ	JPMorgan Chase & Co.	Goldman Sachs	Bank of America	Unum Group	Unum Group
The Hartford	Old Mutual Plc	Capital One Financial	American Express	Lincoln National	Prudential Plc	ING Group	UBS AG
Societe Generale	Unum Group	CNA Financial	Lloyds Banking Group	American Express	Old Mutual Plc	Aviva Plc	RBS
Legal & General	ICICI Bank	Aviva Plc	ICICI Bank	Wells Fargo & Co.	ING Group	Morgan Stanley	JPMorgan Chase & Co.
Unum Group	Macquarie Group	Bayer AG	Scor SE	KB Kookmin Bank	American Financial	Old Mutual Plc	AXA

Appendix 27 Company Risk Ranking Resulted from Expected Shortfall

2007 Q3	2007 Q4	2008 Q1	2008 Q2	2008 Q3	2008 Q4	2009 Q1	2009 Q2
Radian group	MBIA	MBIA	MBIA	AIG	The Hartford	RBS	KBC Bank
MGIC	Radian group	MGIC	Radian group	Radian group	Lincoln National	Lloyds Banking Group	MGIC
Macquarie Group	MGIC	Radian group	MGIC	MGIC	RBS	MGIC	Capital One
MBIA	Capital One	UBS AG	AIG	Morgan Stanley	MGIC	Citigroup Inc.	Bank of America
Cathay Financial	Morgan Stanley	CNA Financial	Macquarie Group	MBIA	Radian group	Lincoln National	AIG
Standard Chartered	Citigroup Inc.	Macquarie Group	RBS	Bank of America	Morgan Stanley	Bank of America	The Hartford
Lincoln National	AIG	ICICI Bank	Standard Chartered	UBS AG	Citigroup Inc.	KBC Bank	Radian group
Prudential Plc	Shinhan Bank	Merck & Co.	Credit Agricole	Macquarie Group	CNA Financial	Barclays	MBIA
Legal & General	Wells Fargo & Co.	AIG	Barclays	Commerzbank AG	MBIA	The Hartford	Citigroup Inc.
Old Mutual Plc	Cisco Systems Inc.	Societe Generale	Capital One	Lincoln National	Unum Group	AIG	Lincoln National
Unum Group	Barclays	QBE Insurance Group	Commerzbank AG	The Hartford	AIG	Aviva Plc	Lloyds Banking Group
Marsh & McLennan	Medtronic	Credit Suisse Group	Morgan Stanley	JPMorgan Chase & Co.	MetLife	Radian group	RBS
MetLife	RBS	RBS	Merck & Co.	Goldman Sachs	Bank of America	MetLife	Aegon N.V.
American Express	Lincoln National	Commerzbank AG	Citigroup Inc.	Citigroup Inc.	ING Group	MBIA	CNA Financial
The Home Depot	ICICI Bank	Allianz SE	Cigna Corporation	Old Mutual Plc	Allstate	Wells Fargo & Co.	Barclays
Morgan Stanley	Goldman Sachs	ING Group	Lloyds Banking	Lloyds Banking	Old Mutual Plc	Capital One	American Express
Barclays	3M	Bayer AG	CNA Financial	Capital One Financial	Aegon N.V.	Legal & General	Wells Fargo & Co.
The Hartford	American Express	AXA	Wells Fargo & Co.	American Express	Cigna Corporation	JPMorgan Chase & Co.	Commerzbank AG
Capital One	Old Mutual Plc	Capital One	JPMorgan Chase & Co.	The Travelers Co.	chubb Limited	ING Group	MetLife
Vodafone Group	Prudential Plc	Citigroup Inc.	Japan Tobacco Inc.	ING Group	Loews Corporation	Commerzbank AG	Morgan Stanley

Appendix 28 Company Risk Ranking Resulted from Beta

2007 Q3	2007 Q4	2008 Q1	2008 Q2	2008 Q3	2008 Q4	2009 Q1	2009 Q2
Radian group	Radian group	MBIA	MBIA	MGIC Corp.	Lincoln National	Lincoln National	Capital One
MGIC	MGIC	Radian group	MGIC Corp.	Radian group	Morgan Stanley	Citigroup Inc.	The Hartford
MBIA	RBS	MGIC	Radian group	AIG	Radian group	The Hartford	MGIC
Prudential Plc	Barclays	Capital One	Morgan Stanley	MBIA	MGIC Corp.	RBS	Radian group
Old Mutual Plc	Capital One	Citigroup Inc.	Commerzbank AG	Bank of America	Prudential Plc	Bank of America	KBC Bank
Morgan Stanley	Morgan Stanley	Morgan Stanley	AIG	Citigroup Inc.	ING Group	Lloyds Banking Group	Lincoln National
American Express	Prudential Plc	American Express	Citigroup Inc.	Capital One Financial	Citigroup Inc.	Aegon N.V.	MBIA
Legal & General	MBIA	Wells Fargo & Co.	Capital One Financial	JPMorgan Chase & Co.	Aegon N.V.	MBIA	Aegon N.V.
Goldman Sachs	Old Mutual Plc	RBS	RBS	RBS	Unum Group	MGIC.	Bank of America
Lincoln National	Goldman Sachs	Old Mutual Plc	American Express	Wells Fargo & Co.	Credit Suisse Group	Barclays	Wells Fargo & Co.
MetLife	Standard Chartered	Commerzbank AG	Prudential Plc	Barclays	Bank of America	MetLife	CNA Financial
Barclays	Citigroup Inc.	Goldman Sachs	Bank of America	Prudential Plc	AXA	ING Group	American Express
Standard Chartered	Lloyds Banking	JPMorgan Chase & Co.	JPMorgan Chase & Co.	Credit Agricole	The Hartford	Wells Fargo & Co.	MetLife
Unum Group	Aviva Plc	Lincoln National	Credit Agricole	Morgan Stanley	Capital One Financial	Radian group	ING Group
Capital One	AIG	Barclays	Macquarie Group	AXA	Deutsche Bank	Morgan Stanley	RBS
Societe Generale	Legal & General	Bank of America	Wells Fargo & Co.	American Express	AIG	Unum Group	AIG
AXA	Societe Generale	AIG	Barclays	UBS AG	MBIA	Aviva Plc	Barclays
BNP Paribas	American Express	Credit Suisse Group	Standard Chartered	Aviva Plc	Standard Chartered	Capital One Financial	Aviva Plc
Commerzbank AG	Commerzbank AG	Aviva Plc	Goldman Sachs	Legal & General	Allstate	JPMorgan Chase & Co.	Lloyds Banking
RBS	BNP Paribas	Credit Agricole	Lloyds Banking Group	Standard Chartered	MetLife	BNP Paribas	AXA

Appendix 29 Company Risk Ranking Resulted from CDS spread

2007 Q3	2007 Q4	2008 Q1	2008 Q2	2008 Q3	2008 Q4	2009 Q1	2009 Q2
Radian group	Radian group	Radian group	MBIA	Radian group	Radian group	Radian group	AIG
MGIC	MBIA	MBIA	Radian group	MBIA	MBIA	Old Mutual Plc	Radian group
MBIA	MGIC	MGIC	MGIC Corp.	MGIC	AIG	MBIA	MBIA
ICICI Bank	Capital One	Capital One	ICICI Bank	AIG	MGIC	MGIC Corp.	MGIC
Capital One Financial	ICICI Bank	ICICI Bank	Capital One Financial	Capital One	ICICI Bank	Lincoln National	Old Mutual Plc
Unum Group	Morgan Stanley	Shinhan Bank	Macquarie Group	ICICI Bank	Old Mutual Plc	AIG	Lincoln National
Morgan Stanley	KBC Bank	Macquarie Group	Morgan Stanley	Morgan Stanley	Lincoln National	The Hartford	The Hartford
CNA Financial	The Home Depot	American Express	Unum Group	Macquarie Group	The Hartford	Legal & General	Legal & General
Goldman Sachs	Unum Group	Morgan Stanley	AIG	American Express	MetLife	MetLife	MetLife
Marsh & McLennan Co.	Shinhan Bank	The Home Depot	Cathay Financial	Shinhan Bank	Morgan Stanley	ICICI Bank	Citigroup Inc.
Macquarie Group	Goldman Sachs	AIG	Old Mutual Plc	KB Kookmin Bank	Shinhan Bank	Macquarie Group	Prudential Plc
KBC Bank	CNA Financial	Unum Group	Shinhan Bank	Goldman Sachs	Macquarie Group	Prudential Plc	ICICI Bank
Old Mutual Plc	Citigroup Inc.	KB Kookmin Bank	The Home Depot	MetLife	KB Kookmin Bank	Shinhan Bank	American Express
The Home Depot	American Express	Aegon N.V.	American Express	Lincoln National	American Express	KB Kookmin Bank	CNA Financial
Commerzbank AG	AIG	Old Mutual Plc	Aegon N.V.	Citigroup Inc.	Aegon N.V.	American Express	Aegon N.V.
AON Plc	Macquarie Group	Lincoln National	KB Kookmin Bank	Unum Group	CNA Financial	Morgan Stanley	Unum Group
JPMorgan Chase & Co.	KB Kookmin Bank	The Hartford	Citigroup Inc.	Cathay Financial	Capital One	Citigroup Inc.	Macquarie Group
Vodafone Group	Cathay Financial	Cathay Financial	Lincoln National	Aegon N.V.	Prudential Plc	Berkshire Hathaway	Shinhan Bank
Cathay Financial	Marsh & McLennan	MetLife	CNA Financial	The Home Depot	BMW	QBE Insurance Group	Berkshire Hathaway
ING Group	Aegon N.V.	Citigroup Inc.	Goldman Sachs	The Hartford	Goldman Sachs	Aegon N.V.	QBE Insurance Group

Appendix 30 Company Risk Ranking Resulted from Z-Score

2007 Q3	2007 Q4	2008 Q1	2008 Q2	2008 Q3	2008 Q4	2009 Q1	2009 Q2
Old Mutual Plc	Amgen Inc	AON Plc	The Travelers Co.	Prudential Plc	Merck & Co.	Pfizer Inc.	AssicurazioniGenerali
The Travelers Co.	Pfizer Inc.	Capital One	Hannover Re SE	Cigna Corporation	Cathay Financial	The Home Depot	BP Plc
AssicurazioniGenerali	Capital One	Radian group	Old Mutual Plc	Aegon N.V.	Old Mutual Plc	BP Plc	Citigroup Inc.
McDonald	Cigna Corporation	Deutsche Telekom AG	MetLife	Cathay Financial	Medtronic	Deutsche Telekom AG	BMW
Prudential Plc	Aegon N.V.	Hannover Re SE	Marsh & McLennan C	Old Mutual Plc	chubb Limited	Total S.A.	American Financial
Scor SE	Allstate	Aetna Inc.	Citigroup Inc.	chubb Limited	Lincoln National	BASF SE	Morgan Stanley
MGIC Corp.	Scor SE	Merck & Co.	AIG	Munich Re Group	Legal & General	AssicurazioniGenerali	Capital One
Munich Re Group	AON Plc	Allianz SE	Munich Re Group	Loews Corporation	Allstate	Wells Fargo & Co.	Deutsche Telekom AG
Unum Group	Munich Re Group	Morgan Stanley	Unum Group	Marsh & McLennan	Allianz SE	BMW	Lincoln National
Aviva Plc	Unum Group	Citigroup Inc.	MBIA	MGIC	Eli Lilly and Co.	Intesa Sanpaolo	Allianz SE
AON Plc	Hannover Re SE	Societe Generale	UBS AG	AON Plc	ING Group	Morgan Stanley	Berkshire Hathaway
Loews Corporation	Radian group	Credit Agricole	AON Plc	MetLife	RBS	Credit Agricole	Scor SE
Marsh & McLennan Co.	Marsh & McLennan C	Loews Corporation	MGIC	The Travelers Co.	MetLife	The Hartford	KBC Bank
AXA	MGIC	Munich Re Group	Credit Agricole	Hannover Re SE	The Travelers Co.	Goldman Sachs	ING Group
ING Group	Aviva Plc	MBIA	Aviva Plc	Vodafone Group	Marsh & McLennan	Capital One	RBS
Allianz SE	Credit Agricole	MetLife	Loews Corporation	ING Group	Credit Agricole	Citigroup Inc.	UBS AG
Radian group	Loews Corporation	Marsh & McLennan C	Aetna Inc.	BNP Paribas	AON Plc	Berkshire Hathaway	Aetna Inc.
Credit Agricole	ING Group	UBS AG	Allianz SE	UBS AG	Aegon N.V.	Commerzbank AG	Loews Corporation
MetLife	Aetna Inc.	Unum Group	Lincoln National	Societe Generale	Unum Group	Hannover Re SE	AON Plc
BNP Paribas	MBIA	MGIC	ING Group	Allianz SE	MGIC	Credit Suisse Group	Munich Re Group

Appendix 31 Results of One-Sample Wilcoxon Signed-Rank Tests on the Systemic Risk Measures

Company	ΔCoRisk SI	ΔCoVaR SI	CDS Granger SI	Equity Granger SI	CDSIRFMax SI
American Express	0.000***	0.000***	0.002***	0.002***	0.002***
Bank of America	0.000***	0.000***	0.002***	0.002***	0.002***
Capital One Financial	0.000***	0.000***	0.002***	0.002***	0.002***
Citigroup Inc.	0.000***	0.000***	0.002***	0.004***	0.002***
Goldman Sachs	0.000***	0.000***	0.002***	0.002***	0.002***
JPMorgan Chase&Co.	0.000***	0.000***	0.002***	0.002***	0.002***
Morgan Stanley	0.000***	0.000***	0.002***	0.004***	0.002***
Wells Fargo & Co.	0.000***	0.000***	0.002***	0.002***	0.002***
Banco Santander	0.000***	0.000***	0.002***	0.002***	0.002***
KBC Bank	0.000***	0.000***	0.002***	0.002***	0.002***
BNP Paribas	0.000***	0.000***	0.002***	0.002***	0.002***
Credit Agricole	0.000***	0.000***	0.002***	0.002***	0.002***
Societe Generale	0.000***	0.000***	0.002***	0.002***	0.002***
Commerzbank AG	0.000***	0.000***	0.002***	0.002***	0.002***
Deutsche Bank	0.000***	0.000***	0.002***	0.002***	0.002***
Intesa Sanpaolo	0.000***	0.000***	0.002***	0.002***	0.002***
UniCredit	0.000***	0.000***	0.002***	0.004***	0.002***
ING Group	0.000***	0.000***	0.002***	0.002***	0.002***
Nordea Bank	0.000***	0.000***	0.002***	0.002***	0.002***
Credit Suisse Group	0.000***	0.000***	0.002***	0.002***	0.002***
UBS AG	0.000***	0.000***	0.002***	0.002***	0.002***
Barclays	0.000***	0.000***	0.002***	0.002***	0.002***
HSBC Holdings	0.000***	0.000***	0.002***	0.002***	0.002***
Lloyds Banking	0.000***	0.000***	0.002***	0.002***	0.002***
RBS	0.000***	0.000***	0.002***	0.002***	0.002***
Standard Chartered	0.000***	0.000***	0.002***	0.002***	0.002***
ANZ	0.000***	0.000***	0.002***	0.002***	0.002***
Macquarie Group	0.000***	0.000***	0.002***	0.002***	0.002***
National Australia	0.000***	0.000***	0.002***	0.002***	0.002***
ICICI Bank	0.000***	0.000***	0.002***	0.002***	0.002***
KB Kookmin Bank	0.000***	0.000***	0.002***	0.002***	0.002***
Shinhan Bank	0.000***	0.000***	0.002***	0.002***	0.002***
Aetna Inc.	0.000***	0.000***	0.002***	0.002***	0.002***
AIG	0.000***	0.000***	0.002***	0.002***	0.002***
Allstate	0.000***	0.000***	0.002***	0.002***	0.002***
American Financial	0.000***	0.000***	0.002***	0.002***	0.002***
Berkshire Hathaway	0.000***	0.000***	0.002***	0.004***	0.002***
Chubb Limited	0.000***	0.000***	0.002***	0.004***	0.002***
Cigna Corporation	0.000***	0.000***	0.002***	0.002***	0.002***
CNA Financial	0.000***	0.000***	0.002***	0.004***	0.002***
The Hartford	0.000***	0.000***	0.002***	0.002***	0.002***
Lincoln National	0.000***	0.000***	0.002***	0.002***	0.002***
Loews Corporation	0.000***	0.000***	0.002***	0.002***	0.002***

Marsh & McLennan	0.000***	0.000***	0.002***	0.002***	0.002***
MBIA	0.000***	0.000***	0.002***	0.002***	0.002***
MetLife	0.000***	0.000***	0.002***	0.002***	0.002***
MGIC	0.000***	0.000***	0.002***	0.002***	0.002***
Radian Group	0.000***	0.000***	0.002***	0.002***	0.002***
The Travelers Co.	0.000***	0.000***	0.002***	0.002***	0.002***
Unum Group	0.000***	0.000***	0.002***	0.002***	0.002***
AXA	0.000***	0.000***	0.002***	0.002***	0.002***
Scor SE	0.000***	0.000***	0.002***	0.002***	0.002***
Allianz SE	0.000***	0.000***	0.002***	0.002***	0.002***
Hannover Re SE	0.000***	0.000***	0.002***	0.002***	0.002***
Munich Re Group	0.000***	0.000***	0.002***	0.002***	0.002***
Assicurazioni Generali	0.000***	0.000***	0.002***	0.002***	0.002***
Aegon N.V.	0.000***	0.000***	0.002***	0.002***	0.002***
AON Plc	0.000***	0.000***	0.002***	0.002***	0.002***
Aviva Plc	0.000***	0.000***	0.002***	0.002***	0.002***
Legal & General	0.000***	0.000***	0.002***	0.002***	0.002***
Old Mutual Plc	0.000***	0.000***	0.002***	0.002***	0.002***
Prudential Plc	0.000***	0.000***	0.002***	0.002***	0.002***
QBE Insurance	0.000***	0.000***	0.002***	0.002***	0.002***
Cathay Financial	0.000***	0.000***	0.002***	0.002***	0.002***
3M	0.000***	0.000***	0.002***	0.002***	0.002***
Altria Group	0.000***	0.000***	0.002***	0.004***	0.002***
Amgen Inc.	0.000***	0.000***	0.002***	0.004***	0.002***
AT&T Inc.	0.000***	0.000***	0.002***	0.002***	0.002***
Cisco Systems	0.000***	0.000***	0.002***	0.002***	0.002***
Coca-Cola	0.000***	0.000***	0.002***	0.002***	0.002***
Eli Lilly and Co.	0.000***	0.000***	0.002***	0.002***	0.002***
Exxon Mobil	0.000***	0.000***	0.002***	0.002***	0.002***
The Home Depot	0.000***	0.000***	0.002***	0.002***	0.002***
Honeywell	0.000***	0.000***	0.002***	0.002***	0.002***
Johnson & Johnson	0.000***	0.000***	0.002***	0.002***	0.002***
McDonald's	0.000***	0.000***	0.002***	0.004***	0.002***
Merck & Co.	0.000***	0.000***	0.002***	0.002***	0.002***
PepsiCo, Inc.	0.000***	0.000***	0.002***	0.002***	0.002***
Pfizer Inc.	0.000***	0.000***	0.002***	0.004***	0.002***
Procter & Gamble	0.000***	0.000***	0.002***	0.002***	0.002***
Walmart	0.000***	0.000***	0.002***	0.002***	0.002***
Walt Disney	0.000***	0.000***	0.002***	0.002***	0.002***
LVMH	0.000***	0.000***	0.002***	0.002***	0.002***
Sanofi S.A.	0.000***	0.000***	0.002***	0.002***	0.002***
Total S.A.	0.000***	0.000***	0.002***	0.002***	0.002***
BASF SE	0.000***	0.000***	0.002***	0.002***	0.002***
Bayer AG	0.000***	0.000***	0.002***	0.002***	0.002***
BMW	0.000***	0.000***	0.002***	0.002***	0.002***
Deutsche Telekom	0.000***	0.000***	0.002***	0.002***	0.002***

Medtronic	0.000***	0.000***	0.002***	0.008***	0.002***
Nestle S.A.	0.000***	0.000***	0.002***	0.002***	0.002***
BP Plc	0.000***	0.000***	0.002***	0.002***	0.002***
AstraZeneca Plc	0.000***	0.000***	0.002***	0.002***	0.002***
Vodafone Group	0.000***	0.000***	0.002***	0.002***	0.002***
Japan Tobacco	0.000***	0.000***	0.002***	0.002***	0.002***
Toyota Motor	0.000***	0.000***	0.002***	0.002***	0.002***

(continued)

Company	EquityIRFMax SI	CDSIRFPrd SI	EquityIRFPrd SI	DiDe SI	ΔCoRisk SV
American Express	0.002***	0.002***	0.002***	0.000***	0.000***
Bank of America	0.002***	0.002***	0.002***	0.000***	0.000***
Capital One Financial	0.002***	0.002***	0.002***	0.000***	0.000***
Citigroup Inc.	0.004***	0.002***	0.004***	0.000***	0.000***
Goldman Sachs	0.002***	0.002***	0.002***	0.000***	0.000***
JPMorgan Chase&Co.	0.002***	0.002***	0.002***	0.000***	0.000***
Morgan Stanley	0.004***	0.002***	0.004***	0.000***	0.000***
Wells Fargo & Co.	0.002***	0.002***	0.002***	0.000***	0.000***
Banco Santander	0.002***	0.002***	0.002***	0.000***	0.000***
KBC Bank	0.002***	0.002***	0.002***	0.000***	0.000***
BNP Paribas	0.002***	0.002***	0.002***	0.000***	0.000***
Credit Agricole	0.002***	0.002***	0.002***	0.000***	0.000***
Societe Generale	0.002***	0.002***	0.002***	0.000***	0.000***
Commerzbank AG	0.002***	0.002***	0.002***	0.000***	0.000***
Deutsche Bank	0.002***	0.002***	0.002***	0.000***	0.000***
Intesa Sanpaolo	0.002***	0.002***	0.002***	0.000***	0.000***
UniCredit	0.004***	0.002***	0.004***	0.000***	0.000***
ING Group	0.002***	0.002***	0.002***	0.000***	0.000***
Nordea Bank	0.002***	0.002***	0.002***	0.000***	0.000***
Credit Suisse Group	0.002***	0.002***	0.002***	0.000***	0.000***
UBS AG	0.002***	0.002***	0.002***	0.000***	0.000***
Barclays	0.002***	0.002***	0.002***	0.000***	0.000***
HSBC Holdings	0.002***	0.002***	0.002***	0.000***	0.000***
Lloyds Banking	0.002***	0.002***	0.002***	0.000***	0.000***
RBS	0.002***	0.002***	0.002***	0.000***	0.000***
Standard Chartered	0.002***	0.002***	0.002***	0.000***	0.000***
ANZ	0.002***	0.002***	0.002***	0.000***	0.000***
Macquarie Group	0.002***	0.002***	0.002***	0.000***	0.000***
National Australia	0.002***	0.002***	0.002***	0.000***	0.000***
ICICI Bank	0.002***	0.002***	0.002***	0.000***	0.000***
KB Kookmin Bank	0.002***	0.002***	0.002***	0.000***	0.000***
Shinhan Bank	0.002***	0.002***	0.002***	0.000***	0.000***
Aetna Inc.	0.002***	0.002***	0.002***	0.000***	0.000***
AIG	0.002***	0.002***	0.002***	0.000***	0.000***
Allstate	0.002***	0.002***	0.002***	0.000***	0.000***
American Financial	0.002***	0.002***	0.002***	0.000***	0.000***

Berkshire Hathaway	0.004***	0.002***	0.004***	0.000***	0.000***
Chubb Limited	0.004***	0.002***	0.004***	0.000***	0.000***
Cigna Corporation	0.002***	0.002***	0.002***	0.000***	0.000***
CNA Financial	0.004***	0.002***	0.004***	0.000***	0.000***
The Hartford	0.002***	0.002***	0.002***	0.000***	0.000***
Lincoln National	0.002***	0.002***	0.002***	0.000***	0.000***
Loews Corporation	0.002***	0.002***	0.002***	0.000***	0.000***
Marsh & McLennan	0.002***	0.002***	0.002***	0.000***	0.000***
MBIA	0.002***	0.002***	0.002***	0.000***	0.000***
MetLife	0.002***	0.002***	0.002***	0.000***	0.000***
MGIC	0.002***	0.002***	0.002***	0.000***	0.000***
Radian Group	0.002***	0.002***	0.002***	0.000***	0.000***
The Travelers Co.	0.002***	0.002***	0.002***	0.000***	0.000***
Unum Group	0.002***	0.002***	0.002***	0.000***	0.000***
AXA	0.002***	0.002***	0.002***	0.000***	0.000***
Scor SE	0.002***	0.002***	0.002***	0.000***	0.000***
Allianz SE	0.002***	0.002***	0.002***	0.000***	0.000***
Hannover Re SE	0.002***	0.002***	0.002***	0.000***	0.000***
Munich Re Group	0.002***	0.002***	0.002***	0.000***	0.000***
Assicurazioni Generali	0.002***	0.002***	0.002***	0.000***	0.000***
Aegon N.V.	0.002***	0.002***	0.002***	0.000***	0.000***
AON Plc	0.002***	0.002***	0.002***	0.000***	0.000***
Aviva Plc	0.002***	0.002***	0.002***	0.000***	0.000***
Legal & General	0.002***	0.002***	0.002***	0.000***	0.000***
Old Mutual Plc	0.002***	0.002***	0.002***	0.000***	0.000***
Prudential Plc	0.002***	0.002***	0.002***	0.000***	0.000***
QBE Insurance	0.002***	0.002***	0.002***	0.000***	0.000***
Cathay Financial	0.002***	0.002***	0.002***	0.000***	0.000***
3M	0.002***	0.002***	0.002***	0.000***	0.000***
Altria Group	0.004***	0.002***	0.004***	0.000***	0.000***
Amgen Inc.	0.004***	0.002***	0.004***	0.000***	0.000***
AT&T Inc.	0.002***	0.002***	0.002***	0.000***	0.000***
Cisco Systems	0.002***	0.002***	0.002***	0.000***	0.000***
Coca-Cola	0.002***	0.002***	0.002***	0.000***	0.000***
Eli Lilly and Co.	0.002***	0.002***	0.002***	0.000***	0.000***
Exxon Mobil	0.002***	0.002***	0.002***	0.000***	0.000***
The Home Depot	0.002***	0.002***	0.002***	0.000***	0.000***
Honeywell	0.002***	0.002***	0.002***	0.000***	0.000***
Johnson & Johnson	0.002***	0.002***	0.002***	0.000***	0.000***
McDonald's	0.004***	0.002***	0.004***	0.000***	0.000***
Merck & Co.	0.002***	0.002***	0.002***	0.000***	0.000***
PepsiCo, Inc.	0.002***	0.002***	0.002***	0.000***	0.000***
Pfizer Inc.	0.004***	0.002***	0.004***	0.000***	0.000***
Procter & Gamble	0.002***	0.002***	0.002***	0.000***	0.000***
Walmart	0.002***	0.002***	0.002***	0.000***	0.000***
Walt Disney	0.002***	0.002***	0.002***	0.000***	0.000***

LVMH	0.002***	0.002***	0.002***	0.000***	0.000***
Sanofi S.A.	0.002***	0.002***	0.002***	0.000***	0.000***
Total S.A.	0.002***	0.002***	0.002***	0.000***	0.000***
BASF SE	0.002***	0.002***	0.002***	0.000***	0.000***
Bayer AG	0.002***	0.002***	0.002***	0.000***	0.000***
BMW	0.002***	0.002***	0.002***	0.000***	0.000***
Deutsche Telekom	0.002***	0.002***	0.002***	0.000***	0.000***
Medtronic	0.008***	0.002***	0.008***	0.000***	0.000***
Nestle S.A.	0.002***	0.002***	0.002***	0.000***	0.000***
BP Plc	0.002***	0.002***	0.002***	0.000***	0.000***
AstraZeneca Plc	0.002***	0.002***	0.002***	0.000***	0.000***
Vodafone Group	0.002***	0.002***	0.002***	0.000***	0.000***
Japan Tobacco	0.002***	0.002***	0.002***	0.000***	0.000***
Toyota Motor	0.002***	0.002***	0.002***	0.000***	0.000***

(continued)

Company	ΔCoVaR SV	CDS Granger SV	Equity Granger SV	CDSIRFMax SV	EquityIRFMax SV
American Express	0.000***	0.002***	0.002***	0.002***	0.002***
Bank of America	0.000***	0.002***	0.002***	0.002***	0.002***
Capital One Financial	0.000***	0.002***	0.002***	0.002***	0.002***
Citigroup Inc.	0.000***	0.002***	0.002***	0.002***	0.002***
Goldman Sachs	0.000***	0.002***	0.002***	0.002***	0.002***
JPMorgan Chase&Co.	0.000***	0.002***	0.002***	0.002***	0.002***
Morgan Stanley	0.000***	0.002***	0.002***	0.002***	0.002***
Wells Fargo & Co.	0.000***	0.002***	0.002***	0.002***	0.002***
Banco Santander	0.000***	0.002***	0.002***	0.002***	0.002***
KBC Bank	0.000***	0.002***	0.002***	0.002***	0.002***
BNP Paribas	0.000***	0.002***	0.002***	0.002***	0.002***
Credit Agricole	0.000***	0.002***	0.002***	0.002***	0.002***
Societe Generale	0.000***	0.002***	0.002***	0.002***	0.002***
Commerzbank AG	0.000***	0.002***	0.002***	0.002***	0.002***
Deutsche Bank	0.000***	0.002***	0.002***	0.002***	0.002***
Intesa Sanpaolo	0.000***	0.002***	0.002***	0.002***	0.002***
UniCredit	0.000***	0.002***	0.002***	0.002***	0.002***
ING Group	0.000***	0.002***	0.002***	0.002***	0.002***
Nordea Bank	0.000***	0.002***	0.002***	0.002***	0.002***
Credit Suisse Group	0.000***	0.002***	0.002***	0.002***	0.002***
UBS AG	0.000***	0.002***	0.002***	0.002***	0.002***
Barclays	0.000***	0.002***	0.002***	0.002***	0.002***
HSBC Holdings	0.000***	0.002***	0.002***	0.002***	0.002***
Lloyds Banking	0.000***	0.002***	0.002***	0.002***	0.002***
RBS	0.000***	0.002***	0.002***	0.002***	0.002***
Standard Chartered	0.000***	0.002***	0.002***	0.002***	0.002***
ANZ	0.000***	0.002***	0.004***	0.002***	0.004***
Macquarie Group	0.000***	0.002***	0.004***	0.002***	0.004***
National Australia	0.000***	0.002***	0.002***	0.002***	0.002***

ICICI Bank	0.000***	0.002***	0.002***	0.002***	0.002***
KB Kookmin Bank	0.000***	0.002***	0.004***	0.002***	0.004***
Shinhan Bank	0.000***	0.002***	0.002***	0.002***	0.002***
Aetna Inc.	0.000***	0.002***	0.002***	0.002***	0.002***
AIG	0.000***	0.002***	0.002***	0.002***	0.002***
Allstate	0.000***	0.002***	0.002***	0.002***	0.002***
American Financial	0.000***	0.002***	0.002***	0.002***	0.002***
Berkshire Hathaway	0.000***	0.002***	0.002***	0.002***	0.002***
Chubb Limited	0.000***	0.002***	0.002***	0.002***	0.002***
Cigna Corporation	0.000***	0.002***	0.002***	0.002***	0.002***
CNA Financial	0.000***	0.002***	0.002***	0.002***	0.002***
The Hartford	0.000***	0.002***	0.002***	0.002***	0.002***
Lincoln National	0.000***	0.002***	0.002***	0.002***	0.002***
Loews Corporation	0.000***	0.002***	0.002***	0.002***	0.002***
Marsh & McLennan	0.000***	0.002***	0.002***	0.002***	0.002***
MBIA	0.000***	0.002***	0.002***	0.002***	0.002***
MetLife	0.000***	0.002***	0.002***	0.002***	0.002***
MGIC	0.000***	0.002***	0.002***	0.002***	0.002***
Radian Group	0.000***	0.002***	0.002***	0.002***	0.002***
The Travelers Co.	0.000***	0.002***	0.002***	0.002***	0.002***
Unum Group	0.000***	0.002***	0.002***	0.002***	0.002***
AXA	0.000***	0.002***	0.002***	0.002***	0.002***
Scor SE	0.000***	0.002***	0.002***	0.002***	0.002***
Allianz SE	0.000***	0.002***	0.002***	0.002***	0.002***
Hannover Re SE	0.000***	0.002***	0.002***	0.002***	0.002***
Munich Re Group	0.000***	0.002***	0.002***	0.002***	0.002***
Assicurazioni Generali	0.000***	0.002***	0.002***	0.002***	0.002***
Aegon N.V.	0.000***	0.002***	0.002***	0.002***	0.002***
AON Plc	0.000***	0.002***	0.002***	0.002***	0.002***
Aviva Plc	0.000***	0.002***	0.002***	0.002***	0.002***
Legal & General	0.000***	0.002***	0.002***	0.002***	0.002***
Old Mutual Plc	0.000***	0.002***	0.002***	0.002***	0.002***
Prudential Plc	0.000***	0.002***	0.002***	0.002***	0.002***
QBE Insurance	0.000***	0.002***	0.002***	0.002***	0.002***
Cathay Financial	0.000***	0.002***	0.004***	0.002***	0.004***
3M	0.000***	0.002***	0.002***	0.002***	0.002***
Altria Group	0.000***	0.002***	0.002***	0.002***	0.002***
Amgen Inc.	0.000***	0.002***	0.002***	0.002***	0.002***
AT&T Inc.	0.000***	0.004***	0.002***	0.004***	0.002***
Cisco Systems	0.000***	0.002***	0.002***	0.002***	0.002***
Coca-Cola	0.000***	0.002***	0.002***	0.002***	0.002***
Eli Lilly and Co.	0.000***	0.002***	0.002***	0.002***	0.002***
Exxon Mobil	0.000***	0.002***	0.002***	0.002***	0.002***
The Home Depot	0.000***	0.002***	0.002***	0.002***	0.002***
Honeywell	0.000***	0.002***	0.002***	0.002***	0.002***
Johnson & Johnson	0.000***	0.002***	0.002***	0.002***	0.002***

McDonald's	0.000***	0.002***	0.002***	0.002***	0.002***
Merck & Co.	0.000***	0.002***	0.002***	0.002***	0.002***
PepsiCo, Inc.	0.000***	0.002***	0.002***	0.002***	0.002***
Pfizer Inc.	0.000***	0.002***	0.002***	0.002***	0.002***
Procter & Gamble	0.000***	0.002***	0.002***	0.002***	0.002***
Walmart	0.000***	0.002***	0.002***	0.002***	0.002***
Walt Disney	0.000***	0.002***	0.002***	0.002***	0.002***
LVMH	0.000***	0.002***	0.002***	0.002***	0.002***
Sanofi S.A.	0.000***	0.002***	0.002***	0.002***	0.002***
Total S.A.	0.000***	0.002***	0.002***	0.002***	0.002***
BASF SE	0.000***	0.002***	0.002***	0.002***	0.002***
Bayer AG	0.000***	0.002***	0.002***	0.002***	0.002***
BMW	0.000***	0.002***	0.002***	0.002***	0.002***
Deutsche Telekom	0.000***	0.002***	0.002***	0.002***	0.002***
Medtronic	0.000***	0.002***	0.002***	0.002***	0.002***
Nestle S.A.	0.000***	0.002***	0.002***	0.002***	0.002***
BP Plc	0.000***	0.002***	0.002***	0.002***	0.002***
AstraZeneca Plc	0.000***	0.002***	0.002***	0.002***	0.002***
Vodafone Group	0.000***	0.002***	0.002***	0.002***	0.002***
Japan Tobacco	0.000***	0.004***	0.002***	0.004***	0.002***
Toyota Motor	0.000***	0.002***	0.002***	0.002***	0.002***

(continued)

Company	CDSIRFPrd SV	EquityIRFPrd SV	DiDe SV	LRMES	SRISK
American Express	0.002***	0.002***	0.000***	0.000***	0.000***
Bank of America	0.002***	0.002***	0.000***	0.000***	0.000***
Capital One Financial	0.002***	0.002***	0.000***	0.000***	0.3199
Citigroup Inc.	0.002***	0.002***	0.000***	0.000***	0.000***
Goldman Sachs	0.002***	0.002***	0.000***	0.000***	0.000***
JPMorgan Chase&Co.	0.002***	0.002***	0.000***	0.000***	0.000***
Morgan Stanley	0.002***	0.002***	0.000***	0.000***	0.000***
Wells Fargo & Co.	0.002***	0.002***	0.000***	0.000***	0.10675
Banco Santander	0.002***	0.002***	0.000***	0.000***	0.000***
KBC Bank	0.002***	0.002***	0.000***	0.000***	0.000***
BNP Paribas	0.002***	0.002***	0.000***	0.000***	0.000***
Credit Agricole	0.002***	0.002***	0.000***	0.000***	0.000***
Societe Generale	0.002***	0.002***	0.000***	0.000***	0.000***
Commerzbank AG	0.002***	0.002***	0.000***	0.000***	0.000***
Deutsche Bank	0.002***	0.002***	0.000***	0.000***	0.000***
Intesa Sanpaolo	0.002***	0.002***	0.000***	0.000***	0.000***
UniCredit	0.002***	0.002***	0.000***	0.000***	0.000***
ING Group	0.002***	0.002***	0.000***	0.000***	0.000***
Nordea Bank	0.002***	0.002***	0.000***	0.000***	0.000***
Credit Suisse Group	0.002***	0.002***	0.000***	0.000***	0.000***
UBS AG	0.002***	0.002***	0.000***	0.000***	0.000***
Barclays	0.002***	0.002***	0.000***	0.000***	0.000***
HSBC Holdings	0.002***	0.002***	0.000***	0.000***	0.000***

Lloyds Banking	0.002***	0.002***	0.000***	0.000***	0.000***
RBS	0.002***	0.002***	0.000***	0.000***	0.000***
Standard Chartered	0.002***	0.002***	0.000***	0.000***	0.000***
ANZ	0.002***	0.004***	0.000***	0.000***	0.037**
Macquarie Group	0.002***	0.004***	0.000***	0.000***	0.17891
National Australia	0.002***	0.002***	0.000***	0.000***	0.001***
ICICI Bank	0.002***	0.002***	0.000***	0.000***	0.000***
KB Kookmin Bank	0.002***	0.004***	0.000***	0.000***	0.000***
Shinhan Bank	0.002***	0.002***	0.000***	0.000***	0.000***
Aetna Inc.	0.002***	0.002***	0.000***	0.000***	0.000***
AIG	0.002***	0.002***	0.000***	0.000***	0.75721
Allstate	0.002***	0.002***	0.000***	0.000***	0.000***
American Financial	0.002***	0.002***	0.000***	0.000***	0.747
Berkshire Hathaway	0.002***	0.002***	0.000***	0.000***	0.000***
Chubb Limited	0.002***	0.002***	0.000***	0.000***	0.000***
Cigna Corporation	0.002***	0.002***	0.000***	0.000***	0.000***
CNA Financial	0.002***	0.002***	0.000***	0.000***	0.001***
The Hartford	0.002***	0.002***	0.000***	0.000***	0.000***
Lincoln National	0.002***	0.002***	0.000***	0.000***	0.000***
Loews Corporation	0.002***	0.002***	0.000***	0.000***	0.000***
Marsh & McLennan	0.002***	0.002***	0.000***	0.000***	0.000***
MBIA	0.002***	0.002***	0.000***	0.000***	0.747
MetLife	0.002***	0.002***	0.000***	0.000***	0.000***
MGIC	0.002***	0.002***	0.000***	0.000***	0.017**
Radian Group	0.002***	0.002***	0.000***	0.000***	0.053*
The Travelers Co.	0.002***	0.002***	0.000***	0.000***	0.000***
Unum Group	0.002***	0.002***	0.000***	0.000***	0.47622
AXA	0.002***	0.002***	0.000***	0.000***	0.000***
Scor SE	0.002***	0.002***	0.000***	0.000***	0.001***
Allianz SE	0.002***	0.002***	0.000***	0.000***	0.000***
Hannover Re SE	0.002***	0.002***	0.000***	0.000***	0.47622
Munich Re Group	0.002***	0.002***	0.000***	0.000***	0.54527
Assicurazioni Generali	0.002***	0.002***	0.000***	0.000***	0.000***
Aegon N.V.	0.002***	0.002***	0.000***	0.000***	0.000***
AON Plc	0.002***	0.002***	0.000***	0.000***	0.000***
Aviva Plc	0.002***	0.002***	0.000***	0.000***	0.000***
Legal & General	0.002***	0.002***	0.000***	0.000***	0.000***
Old Mutual Plc	0.002***	0.002***	0.000***	0.000***	0.000***
Prudential Plc	0.002***	0.002***	0.000***	0.000***	0.000***
QBE Insurance	0.002***	0.002***	0.000***	0.000***	0.000***
Cathay Financial	0.002***	0.004***	0.000***	0.000***	0.2477
3M	0.002***	0.002***	0.000***	0.000***	0.000***
Altria Group	0.002***	0.002***	0.000***	0.000***	0.000***
Amgen Inc.	0.002***	0.002***	0.000***	0.000***	0.000***
AT&T Inc.	0.004***	0.002***	0.000***	0.000***	0.000***
Cisco Systems	0.002***	0.002***	0.000***	0.000***	0.000***

Coca-Cola	0.002***	0.002***	0.000***	0.000***	0.000***
Eli Lilly and Co.	0.002***	0.002***	0.000***	0.000***	0.000***
Exxon Mobil	0.002***	0.002***	0.000***	0.000***	0.000***
The Home Depot	0.002***	0.002***	0.000***	0.000***	0.000***
Honeywell	0.002***	0.002***	0.000***	0.000***	0.000***
Johnson & Johnson	0.002***	0.002***	0.000***	0.000***	0.000***
McDonald's	0.002***	0.002***	0.000***	0.000***	0.000***
Merck & Co.	0.002***	0.002***	0.000***	0.000***	0.000***
PepsiCo, Inc.	0.002***	0.002***	0.000***	0.000***	0.000***
Pfizer Inc.	0.002***	0.002***	0.000***	0.000***	0.000***
Procter & Gamble	0.002***	0.002***	0.000***	0.000***	0.000***
Walmart	0.002***	0.002***	0.000***	0.000***	0.000***
Walt Disney	0.002***	0.002***	0.000***	0.000***	0.000***
LVMH	0.002***	0.002***	0.000***	0.000***	0.000***
Sanofi S.A.	0.002***	0.002***	0.000***	0.000***	0.000***
Total S.A.	0.002***	0.002***	0.000***	0.000***	0.000***
BASF SE	0.002***	0.002***	0.000***	0.000***	0.000***
Bayer AG	0.002***	0.002***	0.000***	0.000***	0.000***
BMW	0.002***	0.002***	0.000***	0.000***	0.000***
Deutsche Telekom	0.002***	0.002***	0.000***	0.000***	0.000***
Medtronic	0.002***	0.002***	0.000***	0.000***	0.000***
Nestle S.A.	0.002***	0.002***	0.000***	0.000***	0.000***
BP Plc	0.002***	0.002***	0.000***	0.000***	0.000***
AstraZeneca Plc	0.002***	0.002***	0.000***	0.000***	0.000***
Vodafone Group	0.002***	0.002***	0.000***	0.000***	0.000***
Japan Tobacco	0.004***	0.002***	0.000***	0.000***	0.000***
Toyota Motor	0.002***	0.002***	0.000***	0.000***	0.000***

Appendix 32 Results of Kruskal Wallis Test on Systemic Risk Meaures

Banks		Insurers		NFIs	
American Express	0.000***	Aetna Inc.	0.000***	3M	0.000***
Bank of America	0.000***	AIG	0.000***	Altria Group	0.000***
Capital One Financial	0.000***	Allstate	0.000***	Amgen Inc.	0.000***
Citigroup Inc.	0.000***	American Financial	0.000***	AT&T Inc.	0.000***
Goldman Sachs	0.000***	Berkshire Hathaway	0.000***	Cisco Systems	0.000***
JPMorgan Chase&Co.	0.000***	Chubb Limited	0.000***	Coca-Cola	0.000***
Morgan Stanley	0.000***	Cigna Corporation	0.000***	Eli Lilly and Co.	0.000***
Wells Fargo & Co.	0.000***	CNA Financial	0.000***	Exxon Mobil	0.000***
Banco Santander	0.000***	The Hartford	0.000***	The Home Depot	0.000***
KBC Bank	0.000***	Lincoln National	0.000***	Honeywell	0.000***
BNP Paribas	0.000***	Loews Corporation	0.000***	Johnson & Johnson	0.000***
Credit Agricole	0.000***	Marsh & McLennan	0.000***	McDonald's	0.000***
Societe Generale	0.000***	MBIA	0.000***	Merck & Co.	0.000***
Commerzbank AG	0.000***	MetLife	0.000***	PepsiCo, Inc.	0.000***
Deutsche Bank	0.000***	MGIC	0.000***	Pfizer Inc.	0.000***
Intesa Sanpaolo	0.000***	Radian Group	0.000***	Procter & Gamble	0.000***
UniCredit	0.000***	The Travelers Co.	0.000***	Walmart	0.000***
ING Group	0.000***	Unum Group	0.000***	Walt Disney	0.000***
Nordea Bank	0.000***	AXA	0.000***	LVMH	0.000***
Credit Suisse Group	0.000***	Scor SE	0.000***	Sanofi S.A.	0.000***
UBS AG	0.000***	Allianz SE	0.000***	Total S.A.	0.000***
Barclays	0.000***	Hannover Re SE	0.000***	BASF SE	0.000***
HSBC Holdings	0.000***	Munich Re Group	0.000***	Bayer AG	0.000***
Lloyds Banking	0.000***	Assicurazioni Generali	0.000***	BMW	0.000***
RBS	0.000***	Aegon N.V.	0.000***	Deutsche Telekom	0.000***
Standard Chartered	0.000***	AON Plc	0.000***	Medtronic	0.000***
ANZ	0.000***	Aviva Plc	0.000***	Nestle S.A.	0.000***
Macquarie Group	0.000***	Legal & General	0.000***	BP Plc	0.000***
National Australia	0.000***	Old Mutual Plc	0.000***	AstraZeneca Plc	0.000***
ICICI Bank	0.000***	Prudential Plc	0.000***	Vodafone Group	0.000***
KB Kookmin Bank	0.000***	QBE Insurance	0.000***	Japan Tobacco	0.000***
Shinhan Bank	0.000***	Cathay Financial	0.000***	Toyota Motor	0.000***

Appendix 33 Results of Kruskal Wallis Test on Both Firm-Level Risk Measures and Systemic Risk Meaures

Banks		Insurers		NFIs	
American Express	0.000***	Aetna Inc.	0.000***	3M	0.000***
Bank of America	0.000***	AIG	0.000***	Altria Group	0.000***
Capital One Financial	0.000***	Allstate	0.000***	Amgen Inc.	0.000***
Citigroup Inc.	0.000***	American Financial	0.000***	AT&T Inc.	0.000***
Goldman Sachs	0.000***	Berkshire Hathaway	0.000***	Cisco Systems	0.000***
JPMorgan Chase&Co.	0.000***	Chubb Limited	0.000***	Coca-Cola	0.000***
Morgan Stanley	0.000***	Cigna Corporation	0.000***	Eli Lilly and Co.	0.000***
Wells Fargo & Co.	0.000***	CNA Financial	0.000***	Exxon Mobil	0.000***
Banco Santander	0.000***	The Hartford	0.000***	The Home Depot	0.000***
KBC Bank	0.000***	Lincoln National	0.000***	Honeywell	0.000***
BNP Paribas	0.000***	Loews Corporation	0.000***	Johnson & Johnson	0.000***
Credit Agricole	0.000***	Marsh & McLennan	0.000***	McDonald's	0.000***
Societe Generale	0.000***	MBIA	0.000***	Merck & Co.	0.000***
Commerzbank AG	0.000***	MetLife	0.000***	PepsiCo, Inc.	0.000***
Deutsche Bank	0.000***	MGIC	0.000***	Pfizer Inc.	0.000***
Intesa Sanpaolo	0.000***	Radian Group	0.000***	Procter & Gamble	0.000***
UniCredit	0.000***	The Travelers Co.	0.000***	Walmart	0.000***
ING Group	0.000***	Unum Group	0.000***	Walt Disney	0.000***
Nordea Bank	0.000***	AXA	0.000***	LVMH	0.000***
Credit Suisse Group	0.000***	Scor SE	0.000***	Sanofi S.A.	0.000***
UBS AG	0.000***	Allianz SE	0.000***	Total S.A.	0.000***
Barclays	0.000***	Hannover Re SE	0.000***	BASF SE	0.000***
HSBC Holdings	0.000***	Munich Re Group	0.000***	Bayer AG	0.000***
Lloyds Banking	0.000***	Assicurazioni Generali	0.000***	BMW	0.000***
RBS	0.000***	Aegon N.V.	0.000***	Deutsche Telekom	0.000***
Standard Chartered	0.000***	AON Plc	0.000***	Medtronic	0.000***
ANZ	0.000***	Aviva Plc	0.000***	Nestle S.A.	0.000***
Macquarie Group	0.000***	Legal & General	0.000***	BP Plc	0.000***
National Australia	0.000***	Old Mutual Plc	0.000***	AstraZeneca Plc	0.000***
ICICI Bank	0.000***	Prudential Plc	0.000***	Vodafone Group	0.000***
KB Kookmin Bank	0.000***	QBE Insurance	0.000***	Japan Tobacco	0.000***
Shinhan Bank	0.000***	Cathay Financial	0.000***	Toyota Motor	0.000***
Banks		Insurers		NFIs	
American Express	0.000***	Aetna Inc.	0.000***	3M	0.000***
Bank of America	0.000***	AIG	0.000***	Altria Group	0.000***
Capital One Financial	0.000***	Allstate	0.000***	Amgen Inc.	0.000***
Citigroup Inc.	0.000***	American Financial	0.000***	AT&T Inc.	0.000***
Goldman Sachs	0.000***	Berkshire Hathaway	0.000***	Cisco Systems	0.000***
JPMorgan Chase&Co.	0.000***	Chubb Limited	0.000***	Coca-Cola	0.000***
Morgan Stanley	0.000***	Cigna Corporation	0.000***	Eli Lilly and Co.	0.000***
Wells Fargo & Co.	0.000***	CNA Financial	0.000***	Exxon Mobil	0.000***
Banco Santander	0.000***	The Hartford	0.000***	The Home Depot	0.000***

KBC Bank	0.000***	Lincoln National	0.000***	Honeywell	0.000***
BNP Paribas	0.000***	Loews Corporation	0.000***	Johnson & Johnson	0.000***
Credit Agricole	0.000***	Marsh & McLennan	0.000***	McDonald's	0.000***
Societe Generale	0.000***	MBIA	0.000***	Merck & Co.	0.000***
Commerzbank AG	0.000***	MetLife	0.000***	PepsiCo, Inc.	0.000***
Deutsche Bank	0.000***	MGIC	0.000***	Pfizer Inc.	0.000***
Intesa Sanpaolo	0.000***	Radian Group	0.000***	Procter & Gamble	0.000***
UniCredit	0.000***	The Travelers Co.	0.000***	Walmart	0.000***
ING Group	0.000***	Unum Group	0.000***	Walt Disney	0.000***
Nordea Bank	0.000***	AXA	0.000***	LVMH	0.000***
Credit Suisse Group	0.000***	Scor SE	0.000***	Sanofi S.A.	0.000***
UBS AG	0.000***	Allianz SE	0.000***	Total S.A.	0.000***
Barclays	0.000***	Hannover Re SE	0.000***	BASF SE	0.000***
HSBC Holdings	0.000***	Munich Re Group	0.000***	Bayer AG	0.000***
Lloyds Banking	0.000***	Assicurazioni Generali	0.000***	BMW	0.000***
RBS	0.000***	Aegon N.V.	0.000***	Deutsche Telekom	0.000***
Standard Chartered	0.000***	AON Plc	0.000***	Medtronic	0.000***
ANZ	0.000***	Aviva Plc	0.000***	Nestle S.A.	0.000***
Macquarie Group	0.000***	Legal & General	0.000***	BP Plc	0.000***
National Australia	0.000***	Old Mutual Plc	0.000***	AstraZeneca Plc	0.000***
ICICI Bank	0.000***	Prudential Plc	0.000***	Vodafone Group	0.000***
KB Kookmin Bank	0.000***	QBE Insurance	0.000***	Japan Tobacco	0.000***
Shinhan Bank	0.000***	Cathay Financial	0.000***	Toyota Motor	0.000***

Appendix 34 Conover-Iman Test on Sector Connectedness Resulted from ΔCoRisk

ΔCoRisk (Pre-crisis)	ΔCoRisk (Crisis)	ΔCoRisk (Post-Crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 62.6872, df = 8, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 16.0337, df = 8, p-value = 0.04	data: x and g Kruskal-Wallis chi-squared = 43.6544, df = 8, p-value = 0
Conover-Iman test(Benjamini-Yekuteili)	Conover-Iman test(Benjamini-Yekuteili)	Conover-Iman test(Benjamini-Yekuteili)
Pairs t statistic (adjusted p-value)	Pairs t statistic (adjusted p-value)	Pairs t statistic (adjusted p-value)
B-B - B-I : 8.755098 (0.0000)***	B-B - B-I : 2.468210 (0.3501)	B-B - B-I : 3.528314 (0.0099)***
B-B - B-N : 2.192528 (0.1737)	B-B - B-N : 3.516880 (0.1226)	B-B - B-N : 4.603165 (0.0003)***
B-I - B-N : -6.562569 (0.0000)***	B-I - B-N : 1.048669 (1.0000)	B-I - B-N : 1.074850 (1.0000)
B-B - I-B : 4.760490 (0.0001)***	B-B - I-B : 1.023092 (1.0000)	B-B - I-B : 2.132176 (0.3680)
B-I - I-B : -3.994607 (0.0013)***	B-I - I-B : -1.445118 (1.0000)	B-I - I-B : -1.396137 (1.0000)
B-N - I-B : 2.567961 (0.0756)	B-N - I-B : -2.493787 (0.3826)	B-N - I-B : -2.470988 (0.1962)
B-B - I-I : 7.223331 (0.0000)***	B-B - I-I : 1.982241 (0.9734)	B-B - I-I : 4.071581 (0.0017)***
B-I - I-I : -1.531766 (0.6486)	B-I - I-I : -0.485968 (1.0000)	B-I - I-I : 0.543266 (1.0000)
B-N - I-I : 5.030802 (0.0000)***	B-N - I-I : -1.534638 (1.0000)	B-N - I-I : -0.531583 (1.0000)
I-B - I-I : 2.462840 (0.0956)*	I-B - I-I : 0.959149 (1.0000)	I-B - I-I : 1.939404 (0.5067)
B-B - I-N : 1.231420 (1.0000)	B-B - I-N : 2.813504 (0.3271)	B-B - I-N : 4.512621 (0.0003)***
B-I - I-N : -7.523678 (0.0000)***	B-I - I-N : 0.345293 (1.0000)	B-I - I-N : 0.984306 (1.0000)
B-N - I-N : -0.961108 (1.0000)	B-N - I-N : -0.703376 (1.0000)	B-N - I-N : -0.090544 (1.0000)
I-B - I-N : -3.529070 (0.0052)***	I-B - I-N : 1.790411 (1.0000)	I-B - I-N : 2.380444 (0.2114)
I-I - I-N : -5.991911 (0.0000)***	I-I - I-N : 0.831262 (1.0000)	I-I - I-N : 0.441039 (1.0000)
B-B - N-B : 6.682708 (0.0000)***	B-B - N-B : 2.519365 (0.4300)	B-B - N-B : 4.760888 (0.0002)***
B-I - N-B : -2.072390 (0.2223)	B-I - N-B : 0.051154 (1.0000)	B-I - N-B : 1.232573 (1.0000)
B-N - N-B : 4.490179 (0.0002)***	B-N - N-B : -0.997515 (1.0000)	B-N - N-B : 0.157722 (1.0000)
I-B - N-B : 1.922217 (0.3011)	I-B - N-B : 1.496272 (1.0000)	I-B - N-B : 2.628711 (0.1394)
I-I - N-B : -0.540623 (1.0000)	I-I - N-B : 0.537123 (1.0000)	I-I - N-B : 0.689306 (1.0000)
I-N - N-B : 5.451287 (0.0000)***	I-N - N-B : -0.294139 (1.0000)	I-N - N-B : 0.248267 (1.0000)
B-B - N-I : 10.04658 (0.0000)***	B-B - N-I : 2.903024 (0.3824)	B-B - N-I : 5.949649 (0.0000)***
B-I - N-I : 1.291489 (0.9402)	B-I - N-I : 0.434814 (1.0000)	B-I - N-I : 2.421335 (0.2055)
B-N - N-I : 7.854059 (0.0000)***	B-N - N-I : -0.613855 (1.0000)	B-N - N-I : 1.346484 (1.0000)
I-B - N-I : 5.286097 (0.0000)***	I-B - N-I : 1.879932 (1.0000)	I-B - N-I : 3.817472 (0.0039)***
I-I - N-I : 2.823256 (0.0391)**	I-I - N-I : 0.920783 (1.0000)	I-I - N-I : 1.878068 (0.5473)
I-N - N-I : 8.815167 (0.0000)***	I-N - N-I : 0.089520 (1.0000)	I-N - N-I : 1.437028 (1.0000)
N-B - N-I : 3.363880 (0.0084)***	N-B - N-I : 0.383659 (1.0000)	N-B - N-I : 1.188761 (1.0000)
B-B - N-N : 3.574122 (0.0047)***	B-B - N-N : 2.570519 (0.4708)	B-B - N-N : 5.508610 (0.0000)***
B-I - N-N : -5.180975 (0.0000)***	B-I - N-N : 0.102309 (1.0000)	B-I - N-N : 1.980295 (0.4921)
B-N - N-N : 1.381593 (0.8285)	B-N - N-N : -0.946360 (1.0000)	B-N - N-N : 0.905444 (1.0000)
I-B - N-N : -1.186368 (1.0000)	I-B - N-N : 1.547427 (1.0000)	I-B - N-N : 3.376433 (0.0149)**
I-I - N-N : -3.649209 (0.0039)***	I-I - N-N : 0.588278 (1.0000)	I-I - N-N : 1.437028 (1.0000)
I-N - N-N : 2.342702 (0.1248)	I-N - N-N : -0.242984 (1.0000)	I-N - N-N : 0.995989 (1.0000)
N-B - N-N : -3.108585 (0.0177)**	N-B - N-N : 0.051154 (1.0000)	N-B - N-N : 0.747722 (1.0000)
N-I - N-N : -6.472465 (0.0000)***	N-I - N-N : -0.332505 (1.0000)	N-I - N-N : -0.441039 (1.0000)

Appendix 35 Conover-Iman Test on Sector Connectedness Resulted from ΔCoVaR

ΔCoVaR (Pre-crisis)	ΔCoVaR (Crisis)	ΔCoVaR (Post-Crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 14.6526, df = 8, p-value = 0.07	data: x and g Kruskal-Wallis chi-squared = 28.1473, df = 8, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 55.249, df = 8, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs t statistic (adjusted p-value)	Pairs t statistic (adjusted p-value)	Pairs t statistic (adjusted p-value)
B-B - B-I : 1.277554 (1.0000)	B-B - B-I : 0.420031 (1.0000)	B-B - B-I : 0.802005 (1.0000)
B-B - B-N : 2.197750 (0.7720)	B-B - B-N : 1.549771 (0.9982)	B-B - B-N : 2.547278 (0.0973)*
B-I - B-N : 0.920196 (1.0000)	B-I - B-N : 1.129740 (1.0000)	B-I - B-N : 1.745272 (0.5170)
B-B - I-B : 0.509234 (1.0000)	B-B - I-B : 0.550386 (1.0000)	B-B - I-B : 1.786284 (0.5168)
B-I - I-B : -0.768319 (1.0000)	B-I - I-B : 0.130354 (1.0000)	B-I - I-B : 0.984279 (1.0000)
B-N - I-B : -1.688515 (1.0000)	B-N - I-B : -0.999385 (1.0000)	B-N - I-B : -0.760993 (1.0000)
B-B - I-I : -0.330555 (1.0000)	B-B - I-I : 0.289676 (1.0000)	B-B - I-I : 1.086048 (1.0000)
B-I - I-I : -1.608110 (1.0000)	B-I - I-I : -0.130354 (1.0000)	B-I - I-I : 0.284043 (1.0000)
B-N - I-I : -2.528306 (0.6715)	B-N - I-I : -1.260094 (1.0000)	B-N - I-I : -1.461229 (0.8753)
I-B - I-I : -0.839790 (1.0000)	I-B - I-I : -0.260709 (1.0000)	I-B - I-I : -0.700235 (1.0000)
B-B - I-N : 1.366893 (1.0000)	B-B - I-N : 1.332513 (1.0000)	B-B - I-N : 2.835878 (0.0508)*
B-I - I-N : 0.089339 (1.0000)	B-I - I-N : 0.912482 (1.0000)	B-I - I-N : 2.033873 (0.3103)
B-N - I-N : -0.830856 (1.0000)	B-N - I-N : -0.217257 (1.0000)	B-N - I-N : 0.288600 (1.0000)
I-B - I-N : 0.857658 (1.0000)	I-B - I-N : 0.782127 (1.0000)	I-B - I-N : 1.049594 (1.0000)
I-I - I-N : 1.697449 (1.0000)	I-I - I-N : 1.042836 (1.0000)	I-I - I-N : 1.749829 (0.5343)
B-B - N-B : 2.287090 (0.9318)	B-B - N-B : 4.040993 (0.0221)**	B-B - N-B : 5.919345 (0.0000)***
B-I - N-B : 1.009535 (1.0000)	B-I - N-B : 3.620961 (0.0294)**	B-I - N-B : 5.117340 (0.0000)***
B-N - N-B : 0.089339 (1.0000)	B-N - N-B : 2.491221 (0.1651)	B-N - N-B : 3.372067 (0.0113)**
I-B - N-B : 1.777855 (1.0000)	I-B - N-B : 3.490607 (0.0222)**	I-B - N-B : 4.133061 (0.0010)***
I-I - N-B : 2.617645 (1.0000)	I-I - N-B : 3.751316 (0.0289)**	I-I - N-B : 4.833297 (0.0001)***
I-N - N-B : 0.920196 (1.0000)	I-N - N-B : 2.708479 (0.1005)	I-N - N-B : 3.083467 (0.0253)***
B-B - N-I : 2.269222 (0.7789)	B-B - N-I : 3.591994 (0.0193)**	B-B - N-I : 5.206958 (0.0000)***
B-I - N-I : 0.991667 (1.0000)	B-I - N-I : 3.171962 (0.0352)**	B-I - N-I : 4.404953 (0.0004)***
B-N - N-I : 0.071471 (1.0000)	B-N - N-I : 2.042222 (0.3784)	B-N - N-I : 2.659680 (0.0798)*
I-B - N-I : 1.759987 (1.0000)	I-B - N-I : 3.041607 (0.0429)**	I-B - N-I : 3.420674 (0.0105)**
I-I - N-I : 2.599778 (0.8328)	I-I - N-I : 3.302317 (0.0297)**	I-I - N-I : 4.120909 (0.0009)***
I-N - N-I : 0.902328 (1.0000)	I-N - N-I : 2.259480 (0.2566)	I-N - N-I : 2.371080 (0.1482)
N-B - N-I : -0.017867 (1.0000)	N-B - N-I : -0.448999 (1.0000)	N-B - N-I : -0.712387 (1.0000)
B-B - N-N : 1.840392 (1.0000)	B-B - N-N : 3.606477 (0.0231)**	B-B - N-N : 5.134049 (0.0000)***
B-I - N-N : 0.562838 (1.0000)	B-I - N-N : 3.186446 (0.0374)**	B-I - N-N : 4.332043 (0.0005)***
B-N - N-N : -0.357357 (1.0000)	B-N - N-N : 2.056706 (0.3877)	B-N - N-N : 2.586770 (0.0923)*
I-B - N-N : 1.331157 (1.0000)	I-B - N-N : 3.056091 (0.0449)**	I-B - N-N : 3.347764 (0.0114)**
I-I - N-N : 2.170948 (0.7055)	I-I - N-N : 3.316800 (0.0325)**	I-I - N-N : 4.048000 (0.0011)***
I-N - N-N : 0.473499 (1.0000)	I-N - N-N : 2.273963 (0.2643)	I-N - N-N : 2.298170 (0.1702)
N-B - N-N : -0.446697 (1.0000)	N-B - N-N : -0.434515 (1.0000)	N-B - N-N : -0.785296 (1.0000)
N-I - N-N : -0.428829 (1.0000)	N-I - N-N : 0.014483 (1.0000)	N-I - N-N : -0.072909 (1.0000)

Appendix 36 Conover-Iman Test on Sector Connectedness Resulted from CDS-Based and Equity-Based Granger-Causality Tests

CDS-based Granger-causality tests	Equity-based Granger-causality tests
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g	data: x and g
Kruskal-Wallis chi-squared = 16.6799, df = 8, p-value = 0.03	Kruskal-Wallis chi-squared = 40.5066, df = 8, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
B-B - B-I : 0.742823 (1.0000)	B-B - B-I : 3.407316 (0.0128)**
B-B - B-N : 0.914940 (1.0000)	B-B - B-N : 4.878657 (0.0003)***
B-I - B-N : 0.172117 (1.0000)	B-I - B-N : 1.471341 (0.9479)
B-B - I-B : 1.440352 (1.0000)	B-B - I-B : -0.475696 (1.0000)
B-I - I-B : 0.697529 (1.0000)	B-I - I-B : -3.883013 (0.0031)***
B-N - I-B : 0.525411 (1.0000)	B-N - I-B : -5.354354 (0.0001)***
B-B - I-I : 0.724705 (1.0000)	B-B - I-I : 2.223605 (0.2418)
B-I - I-I : -0.018117 (1.0000)	B-I - I-I : -1.183710 (1.0000)
B-N - I-I : -0.190235 (1.0000)	B-N - I-I : -2.655051 (0.0844)*
I-B - I-I : -0.715646 (1.0000)	I-B - I-I : 2.699302 (0.0794)*
B-B - I-N : 0.865117 (1.0000)	B-B - I-N : 4.441680 (0.0007)***
B-I - I-N : 0.122294 (1.0000)	B-I - I-N : 1.034363 (1.0000)
B-N - I-N : -0.049823 (1.0000)	B-N - I-N : -0.436977 (1.0000)
I-B - I-N : -0.575235 (1.0000)	I-B - I-N : 4.917376 (0.0003)***
I-I - I-N : 0.140411 (1.0000)	I-I - I-N : 2.218074 (0.2321)
B-B - N-B : 3.007528 (0.2636)	B-B - N-B : 0.370600 (1.0000)
B-I - N-B : 2.264704 (0.6563)	B-I - N-B : -3.036715 (0.0345)**
B-N - N-B : 2.092587 (0.5399)	B-N - N-B : -4.508056 (0.0007)***
I-B - N-B : 1.567175 (1.0000)	I-B - N-B : 0.846297 (1.0000)
I-I - N-B : 2.282822 (0.7533)	I-I - N-B : -1.853004 (0.4832)
I-N - N-B : 2.142410 (0.5872)	I-N - N-B : -4.071079 (0.0020)***
B-B - N-I : 3.089057 (0.4134)	B-B - N-I : 3.318814 (0.0157)**
B-I - N-I : 2.346234 (0.8043)	B-I - N-I : -0.088501 (1.0000)
B-N - N-I : 2.174116 (0.6127)	B-N - N-I : -1.559842 (0.8381)
I-B - N-I : 1.648705 (1.0000)	I-B - N-I : 3.794511 (0.0039)***
I-I - N-I : 2.364351 (1.0000)	I-I - N-I : 1.095208 (1.0000)
I-N - N-I : 2.223940 (0.6212)	I-N - N-I : -1.122865 (1.0000)
N-B - N-I : 0.081529 (1.0000)	N-B - N-I : 2.948213 (0.0418)**
B-B - N-N : 2.137881 (0.5341)	B-B - N-N : 4.286802 (0.0011)***
B-I - N-N : 1.395058 (1.0000)	B-I - N-N : 0.879485 (1.0000)
B-N - N-N : 1.222940 (1.0000)	B-N - N-N : -0.591855 (1.0000)
I-B - N-N : 0.697529 (1.0000)	I-B - N-N : 4.762498 (0.0003)***
I-I - N-N : 1.413175 (1.0000)	I-I - N-N : 2.063196 (0.3178)
I-N - N-N : 1.272764 (1.0000)	I-N - N-N : -0.154878 (1.0000)
N-B - N-N : -0.869646 (1.0000)	N-B - N-N : 3.916201 (0.0031)***
N-I - N-N : -0.951176 (1.0000)	N-I - N-N : 0.967987 (1.0000)

Appendix 37Conover-Iman Test on Sector Connectedness Resulted from IRF

CDS-based IRF maximum values	Equity-based IRF maximum values	CDS-based IRF lasting periods	Equity-based IRF lasting periods
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g	data: x and g	data: x and g	data: x and g
Kruskal-Wallis chi-squared = 20.6488, df = 8, p-value = 0.01 Conover-Iman test (Benjamini-Yekuteili) Pairs: t statistic (adjusted p-value)	Kruskal-Wallis chi-squared = 12.8355, df = 8, p-value = 0.12 Conover-Iman test (Benjamini-Yekuteili) pairs: t statistic (adjusted p-value)	Kruskal-Wallis chi-squared = 3.4632, df = 8, p-value = 0.9 Conover-Iman test (Benjamini-Yekuteili) Pairs: t statistic (adjusted p-value)	Kruskal-Wallis chi-squared = 4.6359, df = 8, p-value = 0.8 Conover-Iman test (Benjamini-Yekuteili) Pairs: t statistic (adjusted p-value)
B-B - B-I : 0.875852 (1.0000)	B-B - B-I : 0.026480 (1.0000)	B-B - B-I : 0.049974 (1.0000)	B-B - B-I : -0.226444 (1.0000)
B-B - B-N : 2.869814 (0.1574)	B-B - B-N : 1.959533 (1.0000)	B-B - B-N : 0.691317 (1.0000)	B-B - B-N : 0.176123 (1.0000)
B-I - B-N : 1.993961 (0.6766)	B-I - B-N : 1.933053 (1.0000)	B-I - B-N : 0.641342 (1.0000)	B-I - B-N : 0.402567 (1.0000)
B-B - I-B : 1.583988 (0.9776)	B-B - I-B : 1.041553 (1.0000)	B-B - I-B : -0.199899 (1.0000)	B-B - I-B : 0.637398 (1.0000)
B-I - I-B : 0.708136 (1.0000)	B-I - I-B : 1.015073 (1.0000)	B-I - I-B : -0.249873 (1.0000)	B-I - I-B : 0.863842 (1.0000)
B-N - I-B : -1.285825 (1.0000)	B-N - I-B : -0.917979 (1.0000)	B-N - I-B : -0.891216 (1.0000)	B-N - I-B : 0.461275 (1.0000)
B-B - I-I : 1.295143 (1.0000)	B-B - I-I : 0.070613 (1.0000)	B-B - I-I : -0.616355 (1.0000)	B-B - I-I : 0.310312 (1.0000)
B-I - I-I : 0.419291 (1.0000)	B-I - I-I : 0.044133 (1.0000)	B-I - I-I : -0.666330 (1.0000)	B-I - I-I : 0.536756 (1.0000)
B-N - I-I : -1.574670 (0.9431)	B-N - I-I : -1.888919 (1.0000)	B-N - I-I : -1.307673 (1.0000)	B-N - I-I : 0.134189 (1.0000)
I-B - I-I : -0.288844 (1.0000)	I-B - I-I : -0.970940 (1.0000)	I-B - I-I : -0.416456 (1.0000)	I-B - I-I : -0.327085 (1.0000)
B-B - I-N : 3.410233 (0.1525)	B-B - I-N : 1.712385 (1.0000)	B-B - I-N : 0.058303 (1.0000)	B-B - I-N : 0.285151 (1.0000)
B-I - I-N : 2.534381 (0.3304)	B-I - I-N : 1.685905 (1.0000)	B-I - I-N : 0.008329 (1.0000)	B-I - I-N : 0.511596 (1.0000)
B-N - I-N : 0.540419 (1.0000)	B-N - I-N : -0.247148 (1.0000)	B-N - I-N : -0.633013 (1.0000)	B-N - I-N : 0.109028 (1.0000)
I-B - I-N : 1.826245 (0.7675)	I-B - I-N : 0.670831 (1.0000)	I-B - I-N : 0.258202 (1.0000)	I-B - I-N : -0.352246 (1.0000)
I-I - I-N : 2.115090 (0.6261)	I-I - I-N : 1.641771 (1.0000)	I-I - I-N : 0.674659 (1.0000)	I-I - I-N : -0.025160 (1.0000)
B-B - N-B : 2.925719 (0.1675)	B-B - N-B : 2.374389 (1.0000)	B-B - N-B : 0.757950 (1.0000)	B-B - N-B : 1.585109 (1.0000)
B-I - N-B : 2.049867 (0.6554)	B-I - N-B : 2.347909 (1.0000)	B-I - N-B : 0.707975 (1.0000)	B-I - N-B : 1.811553 (1.0000)
B-N - N-B : 0.055905 (1.0000)	B-N - N-B : 0.414856 (1.0000)	B-N - N-B : 0.066633 (1.0000)	B-N - N-B : 1.408985 (1.0000)
I-B - N-B : 1.341731 (1.0000)	I-B - N-B : 1.332835 (1.0000)	I-B - N-B : 0.957849 (1.0000)	I-B - N-B : 0.947710 (1.0000)
I-I - N-B : 1.630576 (1.0000)	I-I - N-B : 2.303776 (1.0000)	I-I - N-B : 1.374306 (1.0000)	I-I - N-B : 1.274796 (1.0000)
I-N - N-B : -0.484514 (1.0000)	I-N - N-B : 0.662004 (1.0000)	I-N - N-B : 0.699646 (1.0000)	I-N - N-B : 1.299957 (1.0000)
B-B - N-I : 3.167976 (0.1085)	B-B - N-I : 1.606464 (1.0000)	B-B - N-I : -0.266532 (1.0000)	B-B - N-I : 0.738040 (1.0000)
B-I - N-I : 2.292124 (0.4601)	B-I - N-I : 1.579984 (1.0000)	B-I - N-I : -0.316506 (1.0000)	B-I - N-I : 0.964484 (1.0000)
B-N - N-I : 0.298162 (1.0000)	B-N - N-I : -0.353069 (1.0000)	B-N - N-I : -0.957849 (1.0000)	B-N - N-I : 0.561916 (1.0000)
I-B - N-I : 1.583988 (1.0000)	I-B - N-I : 0.564910 (1.0000)	I-B - N-I : -0.066633 (1.0000)	I-B - N-I : 0.100641 (1.0000)
I-I - N-I : 1.872833 (0.7479)	I-I - N-I : 1.535850 (1.0000)	I-I - N-I : 0.349823 (1.0000)	I-I - N-I : 0.427727 (1.0000)
I-N - N-I : -0.242257 (1.0000)	I-N - N-I : -0.105920 (1.0000)	I-N - N-I : -0.324836 (1.0000)	I-N - N-I : 0.452888 (1.0000)
N-B - N-I : 0.242257 (1.0000)	N-B - N-I : -0.767925 (1.0000)	N-B - N-I : -1.024482 (1.0000)	N-B - N-I : -0.847068 (1.0000)
B-B - N-N : 3.242517 (0.1293)	B-B - N-N : 1.774172 (1.0000)	B-B - N-N : 0.424785 (1.0000)	B-B - N-N : 0.645785 (1.0000)
B-I - N-N : 2.366665 (0.4366)	B-I - N-N : 1.747692 (1.0000)	B-I - N-N : 0.374810 (1.0000)	B-I - N-N : 0.872229 (1.0000)
B-N - N-N : 0.372703 (1.0000)	B-N - N-N : -0.185361 (1.0000)	B-N - N-N : -0.266532 (1.0000)	B-N - N-N : 0.469661 (1.0000)
I-B - N-N : 1.658529 (1.0000)	I-B - N-N : 0.732618 (1.0000)	I-B - N-N : 0.624684 (1.0000)	I-B - N-N : 0.008386 (1.0000)
I-I - N-N : 1.947374 (0.6882)	I-I - N-N : 1.703558 (1.0000)	I-I - N-N : 1.041141 (1.0000)	I-I - N-N : 0.335472 (1.0000)
I-N - N-N : -0.167716 (1.0000)	I-N - N-N : 0.061787 (1.0000)	I-N - N-N : 0.366481 (1.0000)	I-N - N-N : 0.360633 (1.0000)
N-B - N-N : 0.316797 (1.0000)	N-B - N-N : -0.600217 (1.0000)	N-B - N-N : -0.333165 (1.0000)	N-B - N-N : -0.939323 (1.0000)
N-I - N-N : 0.074540 (1.0000)	N-I - N-N : 0.167707 (1.0000)	N-I - N-N : 0.691317 (1.0000)	N-I - N-N : -0.092255 (1.0000)

Appendix 38 Conover-Iman Test on Sector Connectedness Resulted from DiDe

DiDe (Pre-crisis)	DiDe (Crisis)	DiDe (Post-Crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 79.0125, df = 8, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 45.71, df = 8, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 146.0215, df = 8, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs t statistic (adjusted p-value)	Pairs t statistic (adjusted p-value)	Pairs t statistic (adjusted p-value)
B-B - B-I : 8.970110 (0.0000)***	B-B - B-I : 1.357474 (0.9633)	B-B - B-I : 3.348451 (0.0059)***
B-B - B-N : 10.84700 (0.0000)***	B-B - B-N : 1.960796 (0.3550)	B-B - B-N : 4.549030 (0.0001)***
B-I - B-N : 1.876898 (0.3012)	B-I - B-N : 0.603322 (1.0000)	B-I - B-N : 1.200579 (1.0000)
B-B - I-B : -1.096888 (1.0000)	B-B - I-B : -0.471345 (1.0000)	B-B - I-B : 1.162586 (1.0000)
B-I - I-B : -10.06699 (0.0000)***	B-I - I-B : -1.828819 (0.4519)	B-I - I-B : -2.185864 (0.1613)
B-N - I-B : -11.94389 (0.0000)***	B-N - I-B : -2.432141 (0.1413)	B-N - I-B : -3.386444 (0.0054)***
B-B - I-I : -0.024375 (1.0000)	B-B - I-I : -0.773006 (1.0000)	B-B - I-I : -0.316608 (1.0000)
B-I - I-I : -8.994485 (0.0000)***	B-I - I-I : -2.130480 (0.2530)	B-I - I-I : -3.665059 (0.0022)***
B-N - I-I : -10.87138 (0.0000)*	B-N - I-I : -2.733802 (0.0678)*	B-N - I-I : -4.865638 (0.0000)***
I-B - I-I : 1.072513 (1.0000)	I-B - I-I : -0.301661 (1.0000)	I-B - I-I : -1.479194 (0.7294)
B-B - I-N : 2.486280 (0.0750)*	B-B - I-N : -0.226245 (1.0000)	B-B - I-N : 0.886503 (1.0000)
B-I - I-N : -6.483829 (0.0000)***	B-I - I-N : -1.583720 (0.6836)	B-I - I-N : -2.461947 (0.0819)*
B-N - I-N : -8.360728 (0.0000)***	B-N - I-N : -2.187042 (0.2323)	B-N - I-N : -3.662526 (0.0021)***
I-B - I-N : 3.583169 (0.0033)***	I-B - I-N : 0.245099 (1.0000)	I-B - I-N : -0.276082 (1.0000)
I-I - I-N : 2.510655 (0.0728)*	I-I - I-N : 0.546760 (1.0000)	I-I - I-N : 1.203112 (1.0000)
B-B - N-B : 12.96765 (0.0000)***	B-B - N-B : 5.901243 (0.0000)***	B-B - N-B : 14.38162 (0.0000)***
B-I - N-B : 3.997549 (0.0008)***	B-I - N-B : 4.543769 (0.0003)***	B-I - N-B : 11.03317 (0.0000)***
B-N - N-B : 2.120651 (0.1794)	B-N - N-B : 3.940447 (0.0021)***	B-N - N-B : 9.832592 (0.0000)***
I-B - N-B : 14.06454 (0.0000)***	I-B - N-B : 6.372588 (0.0000)***	I-B - N-B : 13.21903 (0.0000)***
I-I - N-B : 12.99203 (0.0000)***	I-I - N-B : 6.674249 (0.0000)***	I-I - N-B : 14.69823 (0.0000)***
I-N - N-B : 10.48137 (0.0000)***	I-N - N-B : 6.127489 (0.0000)***	I-N - N-B : 13.49511 (0.0000)***
B-B - N-I : 16.18519 (0.0000)***	B-B - N-I : 5.712705 (0.0000)***	B-B - N-I : 13.24183 (0.0000)***
B-I - N-I : 7.215088 (0.0000)***	B-I - N-I : 4.355230 (0.0006)***	B-I - N-I : 9.893381 (0.0000)***
B-N - N-I : 5.338190 (0.0000)***	B-N - N-I : 3.751908 (0.0036)***	B-N - N-I : 8.692801 (0.0000)***
I-B - N-I : 17.28208 (0.0000)***	I-B - N-I : 6.184050 (0.0000)***	I-B - N-I : 12.07924 (0.0000)***
I-I - N-I : 16.20957 (0.0000)***	I-I - N-I : 6.485711 (0.0000)***	I-I - N-I : 13.55844 (0.0000)***
I-N - N-I : 13.69891 (0.0000)***	I-N - N-I : 5.938951 (0.0000)***	I-N - N-I : 12.35532 (0.0000)***
N-B - N-I : 3.217539 (0.0100)**	N-B - N-I : -0.188538 (1.0000)	N-B - N-I : -1.139790 (1.0000)
B-B - N-N : 7.580718 (0.0000)***	B-B - N-N : 4.185546 (0.0010)***	B-B - N-N : 10.25304 (0.0000)***
B-I - N-N : -1.389392 (0.7675)	B-I - N-N : 2.828072 (0.0554)*	B-I - N-N : 6.904597 (0.0000)***
B-N - N-N : -3.266290 (0.0089)***	B-N - N-N : 2.224749 (0.2231)	B-N - N-N : 5.704017 (0.0000)***
I-B - N-N : 8.677606 (0.0000)***	I-B - N-N : 4.656891 (0.0003)***	I-B - N-N : 9.090461 (0.0000)***
I-I - N-N : 7.605093 (0.0000)***	I-I - N-N : 4.958552 (0.0001)***	I-I - N-N : 10.56965 (0.0000)***
I-N - N-N : 5.094437 (0.0000)***	I-N - N-N : 4.411792 (0.0005)***	I-N - N-N : 9.366544 (0.0000)***
N-B - N-N : -5.386941 (0.0000)***	N-B - N-N : -1.715697 (0.5478)	N-B - N-N : -4.128574 (0.0004)***
N-I - N-N : -8.604481 (0.0000)***	N-I - N-N : -1.527158 (0.7332)	N-I - N-N : -2.988783 (0.0183)**

Appendix 39 Conover-Iman Test for Sector risk Ranking Resulted from ΔCoRisk Systemic Importance

ΔCoRisk Systemic Importance (Pre-crisis)	ΔCoRisk Systemic Importance (Crisis)	ΔCoRisk Systemic Importance (Post-crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 16.1832, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 4.265, df = 2, p-value = 0.12	data: x and g Kruskal-Wallis chi-squared = 8.4882, df = 2, p-value = 0.01
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pair: t statistic (adjusted p-value)
Insurers - Banks : -4.460792 (0.0004)***	Insurers - Banks : -1.310104 (0.5619)	Insurers - Banks : -2.487579 (0.0427)**
Insurers - NFIs : -5.493042 (0.0000)***	Insurers - NFIs : 0.860925 (0.7315)	Insurers - NFIs : 0.323385 (1.0000)
Banks - NFIs : -1.032249 (0.5704)	Banks - NFIs : 2.171029 (0.2285)	Banks - NFIs : 2.810964 (0.0362)**

Appendix 40 Conover-Iman Test for Sector risk Ranking Resulted from ΔCoVaR Systemic Importance

ΔCoVaR Systemic Importance (Pre-crisis)	ΔCoVaR Systemic Importance (Crisis)	ΔCoVaR Systemic Importance (Post-crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 1.1329, df = 2, p-value = 0.57	data: x and g Kruskal-Wallis chi-squared = 0.96, df = 2, p-value = 0.62	data: x and g Kruskal-Wallis chi-squared = 2.2872, df = 2, p-value = 0.32
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	pairs: t statistic (adjusted p-value)
Insurers - Banks : -0.325022 (1.0000)	Insurers - Banks : 0.000000 (1.0000)	Insurers - Banks : 0.086584 (1.0000)
Insurers - NFIs : 0.700048 (1.0000)	Insurers - NFIs : 0.828266 (1.0000)	Insurers - NFIs : 1.353865 (0.9934)
Banks - NFIs : 1.025071 (1.0000)	Banks - NFIs : 0.828266 (1.0000)	Banks - NFIs : 1.267280 (0.5767)

Appendix 41 Conover-Iman Test for Sector risk Ranking Resulted from ΔCoRisk Systemic Vulnerability

ΔCoRisk Systemic Vulnerability (Pre-crisis)	ΔCoRisk Systemic Vulnerability (Crisis)	ΔCoRisk Systemic Vulnerability (Post-crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 13.3858, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 1.085, df = 2, p-value = 0.58	data: x and g Kruskal-Wallis chi-squared = 9.3588, df = 2, p-value = 0.01
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Insurers - Banks : -1.503033 (0.2648)	Insurers - Banks : 0.034609 (1.0000)	Insurers - Banks : -1.370474 (0.3216)
Insurers - NFIs : 3.206472 (0.0095)***	Insurers - NFIs : 0.899844 (1.0000)	Insurers - NFIs : 1.871867 (0.1811)
Banks - NFIs : 4.709506 (0.0004)***	Banks - NFIs : 0.865234 (1.0000)	Banks - NFIs : 3.242341 (0.0104)***

Appendix 42 Conover-Iman Test for Sector risk Ranking Resulted from ΔCoVaR Systemic Vulnerability

ΔCoVaR Systemic Vulnerability (Pre-crisis)	ΔCoVaR Systemic Vulnerability (Crisis)	ΔCoVaR Systemic Vulnerability (Post-crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 2.449, df = 2, p-value = 0.29	data: x and g Kruskal-Wallis chi-squared = 8.645, df = 2, p-value = 0.01	data: x and g Kruskal-Wallis chi-squared = 17.3717, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Insurers - Banks : 0.973328 (0.9323)	Insurers - Banks : -0.085524 (1.0000)	Insurers - Banks : -0.763227 (0.8217)
Insurers - NFIs : 1.562448 (0.7141)	Insurers - NFIs : 3.036137 (0.0173)**	Insurers - NFIs : 3.716781 (0.0012)***
Banks - NFIs : 0.589119 (1.0000)	Banks - NFIs : 3.121662 (0.0284)**	Banks - NFIs : 4.480009 (0.0002)***

Appendix 43 Conover-Iman Test for Sector risk Ranking Resulted from CDS-Based Granger-Causality Test Systemic Importance

CDS-based Granger-causality test systemic importance(pre-crisis)	CDS-based Granger-causality test systemic importance(crisis)	CDS-based Granger-causality test systemic importance(post-crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g	data: x and g	data: x and g
Kruskal-Wallis chi-squared = 2.5714, df = 2, p-value = 0.28	Kruskal-Wallis chi-squared = 0.0889, df = 2, p-value = 0.96	Kruskal-Wallis chi-squared = 1.14, df = 2, p-value = 0.57
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Insurers - Banks : 0.891132 (0.8039)	Insurers - Banks : -0.259645 (1.0000)	Insurers - Banks : -0.409832 (1.0000)
Insurers - NFIs : 1.782265 (0.9500)	aInsurers - NFIs : -0.129822 (1.0000)	Insurers - NFIs : -1.024581 (1.0000)
Banks - NFIs : 0.891132 (1.0000)	Banks - NFIs : 0.129822 (1.0000)	Banks - NFIs : -0.614748 (1.0000)

Appendix 44 Conover-Iman Test for Sector risk Ranking Resulted from Equity-Based Granger-Causality Test Systemic Importance

Equity-based Granger-causality test systemic importance(pre-crisis)	Equity-based Granger-causality test systemic importance(crisis)	Equity-based Granger-causality test systemic importance(post-crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g	data: x and g	data: x and g
Kruskal-Wallis chi-squared = 4.5714, df = 2, p-value = 0.1	Kruskal-Wallis chi-squared = 3.8222, df = 2, p-value = 0.15	Kruskal-Wallis chi-squared = 8.7957, df = 2, p-value = 0.01
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Insurers - Banks : -2.828427 (0.1215)	Insurers - Banks : -1.429179 (0.5579)	Insurers - Banks : -3.009129 (0.0299)**
Insurers - NFIs : 2.828427 (0.1823)	aInsurers - NFIs : 0.893237 (0.7446)	Insurers - NFIs : 1.397095 (0.3441)
Banks - NFIs : 5.656854 (0.0602)*	Banks - NFIs : 2.322416 (0.3259)	Banks - NFIs : 4.406225 (0.0047)***

Appendix 45 Conover-Iman Test for Sector risk Ranking Resulted from CDS-Based Granger-Causality Test Systemic Vulnerability

CDS-based Granger-causality test systemic vulnerability(pre-crisis)	CDS-based Granger-causality test systemic vulnerability(crisis)	CDS-based Granger-causality test systemic vulnerability(post-crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g	data: x and g	data: x and g
Kruskal-Wallis chi-squared = 2.5714, df = 2, p-value = 0.28	Kruskal-Wallis chi-squared = 2.4889, df = 2, p-value = 0.29	Kruskal-Wallis chi-squared = 5.82, df = 2, p-value = 0.05
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Insurers - Banks : 0.891132 (0.8039)	Insurers - Banks : -0.311085 (1.0000)	Insurers - Banks : -0.770799 (0.8355)
Insurers - NFIs : 1.782265 (0.9500)	Insurers - NFIs : 1.244342 (0.7144)	Insurers - NFIs : 2.055465 (0.1712)
Banks - NFIs : 0.891132 (1.0000)	Banks - NFIs : 1.555427 (0.9396)	Banks - NFIs : 2.826265 (0.0840)*

Appendix 46 Conover-Iman Test for Sector risk Ranking Resulted from Equity-Based Granger-Causality Test Systemic Vulnerability

Equity-based Granger-causality test systemic vulnerability(pre-crisis)	Equity-based Granger-causality test systemic vulnerability(crisis)	Equity-based Granger-causality test systemic vulnerability(post-crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g	data: x and g	data: x and g
Kruskal-Wallis chi-squared = 0.2857, df = 2, p-value = 0.87	Kruskal-Wallis chi-squared = 0.2667, df = 2, p-value = 0.88	Kruskal-Wallis chi-squared = 2.54, df = 2, p-value = 0.28
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Insurers - Banks : 0.213200 (1.0000)	Insurers - Banks : 0.393919 (1.0000)	Insurers - Banks : 1.374791 (0.5344)
Insurers - NFIs : -0.213200 (1.0000)	Insurers - NFIs : 0.393919 (1.0000)	Insurers - NFIs : 1.447149 (0.9541)
Banks - NFIs : -0.426401 (1.0000)	Banks - NFIs : 0.000000 (1.0000)	Banks - NFIs : 0.072357 (1.0000)

Appendix 47 Conover-Iman Test for Sector risk Ranking Resulted from CDS-Based IRF Maximum Values Systemic Importance

CDS-based IRF Maximum Values Systemic importance (pre-crisis)	CDS-based IRF Maximum Values Systemic importance (crisis)	CDS-based IRF Maximum Values Systemic importance (post-crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 2.5714, df = 2, p-value = 0.28	data: x and g Kruskal-Wallis chi-squared = 0.6222, df = 2, p-value = 0.73	data: x and g Kruskal-Wallis chi-squared = 9.74, df = 2, p-value = 0.01
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Insurers - Banks : -0.891132 (0.8039)	Insurers - Banks : -0.134433 (1.0000)	Insurers - Banks : -2.254885 (0.0800)*
Insurers - NFIs : 0.891132 (1.0000)	Insurers - NFIs : 0.537732 (1.0000)	Insurers - NFIs : 2.966954 (0.0324)**
Banks - NFIs : 1.782265 (0.9500)	Banks - NFIs : 0.672166 (1.0000)	Banks - NFIs : 5.221839 (0.0012)***

Appendix 48 Conover-Iman Test for Sector risk Ranking Resulted from Equity-Based IRF Maximum Values Systemic Importance

Equity-based IRF Maximum Values Systemic importance (pre-crisis)	Equity-based IRF Maximum Values Systemic importance (crisis)	Equity-based IRF Maximum Values Systemic importance (post-crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 2, df = 2, p-value = 0.37	data: x and g Kruskal-Wallis chi-squared = 1.8667, df = 2, p-value = 0.39	data: x and g Kruskal-Wallis chi-squared = 4.34, df = 2, p-value = 0.11
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Insurers - Banks : 0.267261 (1.0000)	Insurers - Banks : -0.442325 (1.0000)	Insurers - Banks : -0.078811 (1.0000)
Insurers - NFIs : 1.336306 (1.0000)	Insurers - NFIs : 0.884651 (1.0000)	Insurers - NFIs : 1.970276 (0.1989)
Banks - NFIs : 1.069044 (0.9994)	Banks - NFIs : 1.326977 (1.0000)	Banks - NFIs : 2.049087 (0.3464)

Appendix 49 Conover-Iman Test for Sector risk Ranking Resulted from CDS-Based IRF Maximum Values Systemic Vulnerability

CDS-based IRF Maximum Values Systemic Vulnerability (pre-crisis)	CDS-based IRF Maximum Values Systemic Vulnerability (crisis)	CDS-based IRF Maximum Values Systemic Vulnerability (post-crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 2.5714, df = 2, p-value = 0.28	data: x and g Kruskal-Wallis chi-squared = 1.6889, df = 2, p-value = 0.43	data: x and g Kruskal-Wallis chi-squared = 8.06, df = 2, p-value = 0.02
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Insurers - Banks : 0.891132 (0.8039)	Insurers - Banks : -1.162803 (1.0000)	Insurers - Banks : -2.311586 (0.1082)
Insurers - NFIs : 1.782265 (0.9500)	Insurers - NFIs : -0.145350 (1.0000)	Insurers - NFIs : 1.708564 (0.2076)
Banks - NFIs : 0.891132 (1.0000)	Banks - NFIs : 1.017453 (0.9575)	Banks - NFIs : 4.020151 (0.0093)***

Appendix 50 Conover-Iman Test for Sector risk Ranking Resulted from Equity-Based IRF Maximum Values Systemic Vulnerability

Equity-based IRF Maximum Values Systemic Vulnerability (pre-crisis)	Equity-based IRF Maximum Values Systemic Vulnerability (crisis)	Equity-based IRF Maximum Values Systemic Vulnerability (post-crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 2.5714, df = 2, p-value = 0.28	data: x and g Kruskal-Wallis chi-squared = 1.8667, df = 2, p-value = 0.39	data: x and g Kruskal-Wallis chi-squared = 1.22, df = 2, p-value = 0.54
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Insurers - Banks : -0.891132 (0.8039)	Insurers - Banks : -0.442325 (1.0000)	Insurers - Banks : 0.068518 (1.0000)
Insurers - NFIs : 0.891132 (1.0000)	Insurers - NFIs : 0.884651 (1.0000)	Insurers - NFIs : 0.959264 (1.0000)
Banks - NFIs : 1.782265 (0.9500)	Banks - NFIs : 1.326977 (1.0000)	Banks - NFIs : 0.890745 (1.0000)

Appendix 51 Conover-Iman Test for Sector risk Ranking Resulted from CDS-Based IRF Lasting Periods Systemic Importance

CDS-based IRF Lasting Periods Systemic importance (pre-crisis)	CDS-based IRF Lasting Periods Systemic importance (crisis)	CDS-based IRF Lasting Periods Systemic importance (post-crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 2.5714, df = 2, p-value = 0.28	data: x and g Kruskal-Wallis chi-squared = 1.4222, df = 2, p-value = 0.49	data: x and g Kruskal-Wallis chi-squared = 1.22, df = 2, p-value = 0.54
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Insurers - Banks : -0.891132 (0.8039)	Insurers - Banks : 0.569494 (1.0000)	Insurers - Banks : 0.068518 (1.0000)
Insurers - NFIs : -1.782265 (0.9500)	Insurers - NFIs : 1.138989 (1.0000)	Insurers - NFIs : 0.959264 (1.0000)
Banks - NFIs : -0.891132 (1.0000)	Banks - NFIs : 0.569494 (1.0000)	Banks - NFIs : 0.890745 (1.0000)

Appendix 52 Conover-Iman Test for Sector risk Ranking Resulted from Equity-Based IRF Lasting Periods Systemic Importance

Equity-based IRF Lasting Periods Systemic importance (pre-crisis)	Equity-based IRF Lasting Periods Systemic importance (crisis)	Equity-based IRF Lasting Periods Systemic importance (post-crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 2.5714, df = 2, p-value = 0.28	data: x and g Kruskal-Wallis chi-squared = 3.2889, df = 2, p-value = 0.19	data: x and g Kruskal-Wallis chi-squared = 0.38, df = 2, p-value = 0.83
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Insurers - Banks : 0.891132 (0.8039)	Insurers - Banks : 1.682316 (0.3946)	Insurers - Banks : 0.066372 (1.0000)
Insurers - NFIs : -0.891132 (1.0000)	Insurers - NFIs : 1.850548 (0.6254)	Insurers - NFIs : 0.530978 (1.0000)
Banks - NFIs : -1.782265 (0.9500)	Banks - NFIs : 0.168231 (1.0000)	Banks - NFIs : 0.464606 (1.0000)

Appendix 53 Conover-Iman Test for Sector risk Ranking Resulted from CDS-Based IRF Lasting Periods Systemic Vulenrability

CDS-based IRF Lasting Periods Systemic Vulnerability (pre-crisis)	CDS-based IRF Lasting Periods Systemic Vulnerability (crisis)	CDS-based IRF Lasting Periods Systemic Vulnerability (post-crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 3.7143, df = 2, p-value = 0.16	data: x and g Kruskal-Wallis chi-squared = 1.0667, df = 2, p-value = 0.59	data: x and g Kruskal-Wallis chi-squared = 0.98, df = 2, p-value = 0.61
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Insurers - Banks : -2.041241 (0.3682)	Insurers - Banks : 0.000000 (1.0000)	Insurers - Banks : 0.746728 (1.0000)
Insurers - NFIs : -2.857738 (0.3558)	Insurers - NFIs : 0.832050 (1.0000)	Insurers - NFIs : -0.135768 (1.0000)
Banks - NFIs : -0.816496 (0.8690)	Banks - NFIs : 0.832050 (1.0000)	Banks - NFIs : -0.882497 (1.0000)

Appendix 54 Conover-Iman Test for Sector risk Ranking Resulted from Equity-Based IRF Lasting Periods Systemic Vulenrability

Equity-based IRF Lasting Periods Systemic Vulnerability (pre-crisis)	Equity-based IRF Lasting Periods Systemic Vulnerability (crisis)	Equity-based IRF Lasting Periods Systemic Vulnerability (post-crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 0.8571, df = 2, p-value = 0.65	data: x and g Kruskal-Wallis chi-squared = 2.4889, df = 2, p-value = 0.29	data: x and g Kruskal-Wallis chi-squared = 1.86, df = 2, p-value = 0.39
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Insurers - Banks : -0.682288 (1.0000)	Insurers - Banks : -1.244342 (0.7144)	Insurers - Banks : -0.210905 (1.0000)
Insurers - NFIs : 0.000000 (1.0000)	Insurers - NFIs : 0.311085 (1.0000)	Insurers - NFIs : 1.054526 (0.8591)
Banks - NFIs : 0.682288 (1.0000)	Banks - NFIs : 1.555427 (0.9396)	Banks - NFIs : 1.265431 (1.0000)

Appendix 55 Conover-Iman Test for Sector risk Ranking Resulted from DiDe Systemic Importance

DiDe Systemic Importance (Pre-crisis)	DiDe Systemic Importance (Crisis)	DiDe Systemic Importance (Post-crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 19.8606, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 0.375, df = 2, p-value = 0.83	data: x and g Kruskal-Wallis chi-squared = 1.1726, df = 2, p-value = 0.56
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Insurers - Banks : -7.159820 (0.0000)***	Insurers - Banks : -0.510930 (1.0000)	Insurers - Banks : -1.068912 (1.0000)
Insurers - NFIs : -1.222408 (0.4255)	Insurers - NFIs : 0.000000 (1.0000)	Insurers - NFIs : -0.429125 (1.0000)
Banks - NFIs : 5.937411 (0.0000)***	Banks - NFIs : 0.510930 (1.0000)	Banks - NFIs : 0.639786 (1.0000)

Appendix 56 Conover-Iman Test for Sector risk Ranking Resulted from DiDe Systemic Vulnerability

DiDe Systemic Vulnerability (Pre-crisis)	DiDe Systemic Vulnerability (Crisis)	DiDe Systemic Vulnerability (Post-crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 25.8065, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 14.78, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 44.8829, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	pairs: t statistic (adjusted p-value)
Insurers - Banks : 7.385489 (0.0000)***	Insurers - Banks : 1.808334 (0.1556)	Insurers - Banks : 2.195836 (0.0583)*
Insurers - NFIs : 14.77097 (0.0000)***	Insurers - NFIs : 5.990107 (0.0000)***	Insurers - NFIs : 11.18764 (0.0000)***
Banks - NFIs : 7.385489 (0.0000)***	Banks - NFIs : 4.181773 (0.0012)***	Banks - NFIs : 8.991812 (0.0000)***

Appendix 57 Conover-Iman Test for Sector risk Ranking Resulted from LRMES

LRMES (Pre-crisis)	LRMES (Crisis)	LRMES (Post-crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 5.9071, df = 2, p-value = 0.05	data: x and g Kruskal-Wallis chi-squared = 8.645, df = 2, p-value = 0.01	data: x and g Kruskal-Wallis chi-squared = 21.0813, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Insurers - Banks : -0.741550 (0.8521)	Insurers - Banks : -0.726962 (0.8713)	Insurers - Banks : -1.363855 (0.3254)
Insurers - NFIs : 1.812678 (0.2228)	Insurers - NFIs : 2.651274 (0.0411)**	Insurers - NFIs : 3.931666 (0.0006)***
Banks - NFIs : 2.554228 (0.0913)*	Banks - NFIs : 3.378237 (0.0156)**	Banks - NFIs : 5.295522 (0.0000)***

Appendix 58 Conover-Iman Test for Sector risk Ranking Resulted from SRISK

SRISK (Pre-crisis)	SRISK (Crisis)	SRISK (Post-crisis)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 25.8065, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 20.48, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 57.791, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Insurers - Banks : -7.385489 (0.0000)***	Insurers - Banks : -6.531972 (0.0000)***	Insurers - Banks : -11.23658 (0.0000)***
Insurers - NFIs : 7.385489 (0.0000)***	Insurers - NFIs : 6.531972 (0.0000)***	Insurers - NFIs : 11.23658 (0.0000)***
Banks - NFIs : 14.77097 (0.0000)***	Banks - NFIs : 13.06394 (0.0000)***	Banks - NFIs : 22.47317 (0.0000)***

Appendix 59 Conover-Iman Test for Risk Ranking among Time Periods Resulted from ΔCoRisk Systemic Importance

ΔCoRisk Systemic Importance (banks)	ΔCoRisk Systemic Importance (insurers)	ΔCoRisk Systemic Importance(NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g	data: x and g	data: x and g
Kruskal-Wallis chi-squared = 47.7425, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 48.5326, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 54.5843, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : 9.618528 (0.0000)***	Crisis - Post-crisis : 9.528558 (0.0000)***	Crisis - Post-crisis : 10.91136 (0.0000)***
Crisis - Pre-crisis : 5.847914 (0.0000)***	Crisis - Pre-crisis : 6.944865 (0.0000)***	Crisis - Pre-crisis : 3.240057 (0.0030)***
Post-crisis - Pre-crisis : -3.770614 (0.0005)***	Post-crisis - Pre-crisis : -2.583693 (0.0208)**	Post-crisis - Pre-crisis : -7.671311 (0.0000)***

Appendix 60 Conover-Iman Test for Risk Ranking among Time Periods Resulted from ΔCoVaR Systemic Importance

ΔCoVaR Systemic Importance (banks)	ΔCoVaR Systemic Importance (insurers)	ΔCoVaR Systemic Importance(NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g	data: x and g	data: x and g
Kruskal-Wallis chi-squared = 63.1798, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 76.3306, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 75.3135, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : 7.034590 (0.0000)***	Crisis - Post-crisis : 9.824822 (0.0000)***	Crisis - Post-crisis : 9.460361 (0.0000)***
Crisis - Pre-crisis : 13.58588 (0.0000)***	Crisis - Pre-crisis : 19.49941 (0.0000)***	Crisis - Pre-crisis : 18.86220 (0.0000)***
Post-crisis - Pre-crisis : 6.551298 (0.0000)***	Post-crisis - Pre-crisis : 9.674595 (0.0000)***	Post-crisis - Pre-crisis : 9.401843 (0.0000)***

Appendix 61 Conover-Iman Test for Risk Ranking among Time Periods Resulted from ΔCoRisk Systemic Vulnerability

ΔCoRisk Systemic Vulnerability (banks)	ΔCoRisk Systemic Vulnerability (insurers)	ΔCoRisk Systemic Vulnerability(NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g	data: x and g	data: x and g
Kruskal-Wallis chi-squared = 72.0044, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 41.8208, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 64.9505, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : 17.06436 (0.0000)***	Crisis - Post-crisis : 8.550936 (0.0000)***	Crisis - Post-crisis : 14.16988 (0.0000)***
Crisis - Pre-crisis : 8.437429 (0.0000)***	Crisis - Pre-crisis : 4.159754 (0.0001)***	Crisis - Pre-crisis : 7.499380 (0.0000)***
Post-crisis - Pre-crisis : -8.626933 (0.0000)***	Post-crisis - Pre-crisis : -4.391181 (0.0001)***	Post-crisis - Pre-crisis : -6.670501 (0.0000)***

Appendix 62 Conover-Iman Test for Risk Ranking among Time Periods Resulted from ΔCoVaR Systemic Vulnerability

ΔCoVaR Systemic Vulnerability (banks)	ΔCoVaR Systemic Vulnerability (insurers)	ΔCoVaR Systemic Vulnerability(NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g	data: x and g	data: x and g
Kruskal-Wallis chi-squared = 62.3032, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 68.325, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 60.201, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : 6.576397 (0.0000)***	Crisis - Post-crisis : 6.702830 (0.0000)***	Crisis - Post-crisis : 6.462712 (0.0000)***
Crisis - Pre-crisis : 13.31171 (0.0000)***	Crisis - Pre-crisis : 15.39137 (0.0000)***	Crisis - Pre-crisis : 12.68334 (0.0000)***
Post-crisis - Pre-crisis : 6.735320 (0.0000)***	Post-crisis - Pre-crisis : 8.688544 (0.0000)***	Post-crisis - Pre-crisis : 6.220636 (0.0000)***

Appendix 63 Conover-Iman Test for Risk Ranking among Time Periods Resulted from CDS-Based Granger-Causality Test Systemic Importance

CDS-based Granger-causality test systemic importance(banks)	CDS-based Granger-causality test systemic importance(insurers)	CDS-based Granger-causality test systemic importance(NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g	data: x and g	data: x and g
Kruskal-Wallis chi-squared = 17.668, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 24.8369, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 56.117, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : 2.367222 (0.0550)*	Crisis - Post-crisis : 2.911358 (0.0124)**	Crisis - Post-crisis : 2.019637 (0.0849)*
Crisis - Pre-crisis : 4.608947 (0.0001)***	Crisis - Pre-crisis : 5.737468 (0.0000)***	Crisis - Pre-crisis : 10.88938 (0.0000)***
Post-crisis - Pre-crisis : 2.241725 (0.0502)*	Post-crisis - Pre-crisis : 2.826109 (0.0106)**	Post-crisis - Pre-crisis : 8.869749 (0.0000)***

Appendix 64 Conover-Iman Test for Risk Ranking among Time Periods Resulted from Equity-Based Granger-Causality Test Systemic Importance

Equity-based Granger-causality test systemic importance(banks)	Equity-based Granger-causality test systemic importance(insurers)	Equity-based Granger-causality test systemic importance(NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g	data: x and g	data: x and g
Kruskal-Wallis chi-squared = 11.0184, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 7.872, df = 2, p-value = 0.02	Kruskal-Wallis chi-squared = 20.8075, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : 3.053040 (0.0162)**	Crisis - Post-crisis : 2.346069 (0.0580)*	Crisis - Post-crisis : 3.902272 (0.0005)***
Crisis - Pre-crisis : 2.996371 (0.0096)***	Crisis - Pre-crisis : 2.647442 (0.0524)*	Crisis - Pre-crisis : 4.804343 (0.0000)***
Post-crisis - Pre-crisis : -0.056668 (1.0000)	Post-crisis - Pre-crisis : 0.301372 (1.0000)	Post-crisis - Pre-crisis : 0.902070 (0.6771)

Appendix 65Conover-Iman Test for Risk Ranking among Time Periods Resulted from CDS-Based Granger-Causality Test Systemic Vulnerability

CDS-based Granger-causality test systemic vulnerability(banks)	CDS-based Granger-causality test systemic vulnerability(insurers)	CDS-based Granger-causality test systemic vulnerability(NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g	data: x and g	data: x and g
Kruskal-Wallis chi-squared = 31.499, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 32.759, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 40.5879, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : 0.448035 (1.0000)	Crisis - Post-crisis : 2.391677 (0.0344)**	Crisis - Post-crisis : 4.511533 (0.0001)***
Crisis - Pre-crisis : 6.093282 (0.0000)***	Crisis - Pre-crisis : 6.889786 (0.0000)***	Crisis - Pre-crisis : 8.319056 (0.0000)***
Post-crisis - Pre-crisis : 5.645247 (0.0000)***	Post-crisis - Pre-crisis : 4.498109 (0.0001)***	Post-crisis - Pre-crisis : 3.807522 (0.0005)***

Appendix 66 Conover-Iman Test for Risk Ranking among Time Periods Resulted from Equity-Based Granger-Causality Test Systemic Vulnerability

Equity-based Granger-causality test systemic vulnerability(banks)	Equity-based Granger-causality test systemic vulnerability(insurers)	Equity-based Granger-causality test systemic vulnerability(NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g	data: x and g	data: x and g
Kruskal-Wallis chi-squared = 11.8017, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 19.074, df = 2, p-value = 0	Kruskal-Wallis chi-squared = 16.7802, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : 1.376029 (0.3155)	Crisis - Post-crisis : 2.835966 (0.0154)**	Crisis - Post-crisis : 2.994762 (0.0097)***
Crisis - Pre-crisis : 3.599029 (0.0028)***	Crisis - Pre-crisis : 4.807733 (0.0000)***	Crisis - Pre-crisis : 4.367362 (0.0002)***
Post-crisis - Pre-crisis : 2.222999 (0.0788)*	Post-crisis - Pre-crisis : 1.971766 (0.0946)*	Post-crisis - Pre-crisis : 1.372599 (0.3175)

Appendix 67 Conover-Iman Test for Risk Ranking among Time Periods Resulted from CDS-Based IRF Maximum Values Systemic Importance

CDS-based IRF Maximum Values Systemic Importance (banks)	CDS-based IRF Maximum Values Systemic Importance (insurers)	CDS-based IRF Maximum Values Systemic Importance(NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 64.8825, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 54.291, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 63.1223, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : -2.507484 (0.0255)**	Crisis - Post-crisis : 0.094951 (1.0000)	Crisis - Post-crisis : 2.996775 (0.0064)***
Crisis - Pre-crisis : 10.81056 (0.0000)***	Crisis - Pre-crisis : 9.691870 (0.0000)***	Crisis - Pre-crisis : 12.96047 (0.0000)***
Post-crisis - Pre-crisis : 13.31805 (0.0000)***	Post-crisis - Pre-crisis : 9.596918 (0.0000)***	Post-crisis - Pre-crisis : 9.963703 (0.0000)***

Appendix 68 Conover-Iman Test for Risk Ranking among Time Periods Resulted from Equity-Based IRF Maximum Values Systemic Importance

Equity-based IRF Maximum Values Systemic Importance (banks)	Equity-based IRF Maximum Values Systemic Importance (insurers)	Equity-based IRF Maximum Values Systemic Importance(NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 52.7282, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 45.1653, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 48.5739, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : 0.565736 (1.0000)	Crisis - Post-crisis : 0.367795 (1.0000)	Crisis - Post-crisis : 2.476874 (0.0276)**
Crisis - Pre-crisis : 9.597549 (0.0000)***	Crisis - Pre-crisis : 8.128269 (0.0000)***	Crisis - Pre-crisis : 9.507385 (0.0000)***
Post-crisis - Pre-crisis : 9.031813 (0.0000)***	Post-crisis - Pre-crisis : 7.760474 (0.0000)***	Post-crisis - Pre-crisis : 7.030511 (0.0000)***

Appendix 69 Conover-Iman Test for Risk Ranking among Time Periods Resulted from CDS-Based IRF Maximum Values Systemic Vulnerability

CDS-based IRF Maximum Values Systemic Vulnerability (banks)	CDS-based IRF Maximum Values Systemic Vulnerability (insurers)	CDS-based IRF Maximum Values Systemic Vulnerability(NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 60.9675, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 47.6166, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 67.8425, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : 0.459902 (1.0000)	Crisis - Post-crisis : 0.898970 (0.6801)	Crisis - Post-crisis : 5.513704 (0.0000)***
Crisis - Pre-crisis : 11.40112 (0.0000)***	Crisis - Pre-crisis : 8.785389 (0.0000)***	Crisis - Pre-crisis : 15.06304 (0.0000)***
Post-crisis - Pre-crisis : 10.94122 (0.0000)***	Post-crisis - Pre-crisis : 7.886419 (0.0000)***	Post-crisis - Pre-crisis : 9.549337 (0.0000)***

Appendix 70 Conover-Iman Test for Risk Ranking among Time Periods Resulted from Equity-Based IRF Maximum Values Systemic Vulnerability

Equity-based IRF Maximum Values Systemic Vulnerability (banks)	Equity-based IRF Maximum Values Systemic Vulnerability (insurers)	Equity-based IRF Maximum Values Systemic Vulnerability(NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 31.1894, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 41.9891, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 43.9384, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : 1.782255 (0.1429)	Crisis - Post-crisis : 1.372935 (0.3173)	Crisis - Post-crisis : 1.919696 (0.1063)
Crisis - Pre-crisis : 6.522296 (0.0000)***	Crisis - Pre-crisis : 8.023648 (0.0000)***	Crisis - Pre-crisis : 8.526602 (0.0000)***
Post-crisis - Pre-crisis : 4.740041 (0.0000)***	Post-crisis - Pre-crisis : 6.650713 (0.0000)***	Post-crisis - Pre-crisis : 6.606905 (0.0000)***

Appendix 71 Conover-Iman Test for Risk Ranking among Time Periods Resulted from CDS-Based IRF Lasting Periods Systemic Importance

CDS-based IRF Lasting Periods Systemic Importance (banks)	CDS-based IRF Lasting Periods Systemic Importance (insurers)	CDS-based IRF Lasting Periods Systemic Importance(NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 50.9601, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 39.955, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 60.5261, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : 2.014912 (0.0858)*	Crisis - Post-crisis : 3.295438 (0.0026)***	Crisis - Post-crisis : -0.987597 (0.5975)
Crisis - Pre-crisis : -7.805339 (0.0000)***	Crisis - Pre-crisis : -4.870249 (0.0000)***	Crisis - Pre-crisis : -11.52688 (0.0000)***
Post-crisis - Pre-crisis : -9.820251 (0.0000)***	Post-crisis - Pre-crisis : -8.165688 (0.0000)***	Post-crisis - Pre-crisis : -10.53929 (0.0000)***

Appendix 72 Conover-Iman Test for Risk Ranking among Time Periods Resulted from Equity-Based IRF Lasting Periods Systemic Importance

Equity-based IRF Lasting Periods Systemic Importance (banks)	Equity-based IRF Lasting Periods Systemic Importance (insurers)	Equity-based IRF Lasting Periods Systemic Importance(NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 36.4391, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 30.4419, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 7.8968, df = 2, p-value = 0.02
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : 2.702991 (0.0150)**	Crisis - Post-crisis : 4.152405 (0.0002)***	Crisis - Post-crisis : 2.591883 (0.0610)*
Crisis - Pre-crisis : 7.509566 (0.0000)***	Crisis - Pre-crisis : 6.543673 (0.0000)***	Crisis - Pre-crisis : 2.429600 (0.0468)**
Post-crisis - Pre-crisis : 4.806574 (0.0000)***	Post-crisis - Pre-crisis : 2.391268 (0.0345)**	Post-crisis - Pre-crisis : -0.162282 (1.0000)

Appendix 73 Conover-Iman Test for Risk Ranking among Time Periods Resulted from CDS-Based IRF Lasting Periods Systemic Vulnerability

CDS-based IRF Lasting Periods Systemic Vulnerability (banks)	CDS-based IRF Lasting Periods Systemic Vulnerability (insurers)	CDS-based IRF Lasting Periods Systemic Vulnerability(NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 57.7541, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 44.656, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 65.2254, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : 3.084399 (0.0049)***	Crisis - Post-crisis : 1.140481 (0.4712)	Crisis - Post-crisis : -4.861366 (0.0000)***
Crisis - Pre-crisis : -8.508689 (0.0000)***	Crisis - Pre-crisis : -7.233216 (0.0000)***	Crisis - Pre-crisis : -14.05276 (0.0000)***
Post-crisis - Pre-crisis : -11.59308 (0.0000)***	Post-crisis - Pre-crisis : -8.373698 (0.0000)***	Post-crisis - Pre-crisis : -9.191393 (0.0000)***

Appendix 74 Conover-Iman Test for Risk Ranking among Time Periods Resulted from Equity-Based IRF Lasting Periods Systemic Vulnerability

Equity-based IRF Lasting Periods Systemic Vulnerability (banks)	Equity-based IRF Lasting Periods Systemic Vulnerability (insurers)	Equity-based IRF Lasting Periods Systemic Vulnerability(NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 14.7947, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 32.7402, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 27.7988, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : 2.256503 (0.0725)*	Crisis - Post-crisis : 3.405739 (0.0018)***	Crisis - Post-crisis : 3.916855 (0.0005)***
Crisis - Pre-crisis : 4.136117 (0.0004)***	Crisis - Pre-crisis : 6.992459 (0.0000)***	Crisis - Pre-crisis : 6.123386 (0.0000)***
Post-crisis - Pre-crisis : 1.879614 (0.1160)	Post-crisis - Pre-crisis : 3.586720 (0.0015)***	Post-crisis - Pre-crisis : 2.206530 (0.0546)*

Appendix 75 Conover-Iman Test for Risk Ranking among Time Periods Resulted from DiDe Systemic Importance

DiDe Systemic Importance (banks)	DiDe Systemic Importance (insurers)	DiDe Systemic Importance(NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 34.3969, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 45.5142, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 53.6483, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : 1.912192 (0.1080)	Crisis - Post-crisis : 1.254903 (0.3899)	Crisis - Post-crisis : 1.278578 (0.3744)
Crisis - Pre-crisis : 7.026196 (0.0000)***	Crisis - Pre-crisis : 8.562872 (0.0000)***	Crisis - Pre-crisis : 10.08731 (0.0000)***
Post-crisis - Pre-crisis : 5.114003 (0.0000)***	Post-crisis - Pre-crisis : 7.307968 (0.0000)***	Post-crisis - Pre-crisis : 8.808733 (0.0000)***

Appendix 76 Conover-Iman Test for Risk Ranking among Time Periods Resulted from DiDe Systemic Vulnerability

DiDe Systemic Vulnerability (banks)	DiDe Systemic Vulnerability (insurers)	DiDe Systemic Vulnerability(NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 44.2812, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 25.8375, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 13.3647, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : -0.644083 (0.9554)	Crisis - Post-crisis : 0.327812 (1.0000)	Crisis - Post-crisis : 1.379348 (0.3137)
Crisis - Pre-crisis : 7.461647 (0.0000)***	Crisis - Pre-crisis : 5.260615 (0.0000)***	Crisis - Pre-crisis : 3.850681 (0.0012)***
Post-crisis - Pre-crisis : 8.105730 (0.0000)***	Post-crisis - Pre-crisis : 4.932803 (0.0000)***	Post-crisis - Pre-crisis : 2.471333 (0.0420)**

Appendix 77 Conover-Iman Test for Risk Ranking among Time Periods Resulted from LRMES

LRMES (banks)	LRMES (insurers)	LRMES(NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 74.2053, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 62.5284, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 54.3664, df = 2, p-value = 0
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : 9.935528 (0.0000)***	Crisis - Post-crisis : 6.508033 (0.0000)***	Crisis - Post-crisis : 7.318071 (0.0000)***
Crisis - Pre-crisis : 18.19141 (0.0000)***	Crisis - Pre-crisis : 13.38057 (0.0000)***	Crisis - Pre-crisis : 10.94995 (0.0000)***
Post-crisis - Pre-crisis : 8.255883 (0.0000)***	Post-crisis - Pre-crisis : 6.872544 (0.0000)***	Post-crisis - Pre-crisis : 3.631881 (0.0008)***

Appendix 78 Conover-Iman Test for Risk Ranking among Time Periods Resulted from SRISK

SRISK (banks)	SRISK (insurers)	SRISK(NFIs)
Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test	Kruskal-Wallis rank sum test
data: x and g Kruskal-Wallis chi-squared = 15.469, df = 2, p-value = 0	data: x and g Kruskal-Wallis chi-squared = 4.9221, df = 2, p-value = 0.09	data: x and g Kruskal-Wallis chi-squared = 3.7498, df = 2, p-value = 0.15
Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)	Conover-Iman test (Benjamini-Yekuteili)
Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)	Pairs: t statistic (adjusted p-value)
Crisis - Post-crisis : 0.800638 (0.7799)	Crisis - Post-crisis : 0.683916 (0.9088)	Crisis - Post-crisis : 1.658000 (0.2769)
Crisis - Pre-crisis : 4.017748 (0.0007)***	Crisis - Pre-crisis : 2.202209 (0.1657)	Crisis - Pre-crisis : 1.725951 (0.4822)
Post-crisis - Pre-crisis : 3.217109 (0.0049)***	Post-crisis - Pre-crisis : 1.518293 (0.3639)	Post-crisis - Pre-crisis : 0.067950 (1.0000)

Appendix 79 Rank Correlations between the Systemic Risk Measures Based on Cross-Sectional Data

Cross section		ΔCoRisk SI	ΔCoVaR SI	CDSGranger SI	EquityGranger SI	CDSIRFMax SI
ΔCoRisk SI	Spearman's ρ	1.000				
	P value	1.000				
ΔCoVaR SI	Spearman's ρ	0.276	1.000			
	P value	0.007***	1.000			
CDSGranger SI	Spearman's ρ	0.065	-0.286	1.000		
	P value	0.529	0.005***	1.000		
EquityGranger SI	Spearman's ρ	0.353	-0.122	0.511	1.000	
	P value	0.000***	0.236	0.000***	1.000	
CDSIRFMax SI	Spearman's ρ	0.506	0.658	-0.182	0.124	1.000
	P value	0.000***	0.000***	0.076*	0.229	1.000
EquityIRFMax SI	Spearman's ρ	0.367	0.923	-0.279	-0.067	0.676
	P value	0.000***	0.000***	0.006***	0.517	0.000***
CDSIRFPrd SI	Spearman's ρ	-0.052	0.143	-0.228	-0.058	-0.016
	P value	0.616	0.163	0.025**	0.572	0.873
EquityIRFPrd SI	Spearman's ρ	-0.146	0.215	-0.430	-0.406	-0.007
	P value	0.155	0.035**	0.000***	0.000***	0.948
DiDe SI	Spearman's ρ	0.396	0.792	-0.185	-0.169	0.484
	P value	0.000***	0.000***	0.071*	0.099*	0.000***
ΔCoRisk SV	Spearman's ρ	0.224	0.165	0.116	0.465	0.452
	P value	0.029**	0.108	0.259	0.000***	0.000***
ΔCoVaR SV	Spearman's ρ	0.147	0.762	-0.426	-0.105	0.669
	P value	0.154	0.000***	0.000***	0.307	0.000***
CDSGranger SV	Spearman's ρ	0.243	0.513	-0.439	-0.294	0.734
	P value	0.017**	0.000***	0.000***	0.004***	0.000***
EquityGranger SV	Spearman's ρ	-0.207	0.343	-0.431	-0.438	0.052
	P value	0.043**	0.001***	0.000***	0.000***	0.618
CDSIRFMax SV	Spearman's ρ	0.611	0.603	-0.209	0.115	0.936
	P value	0.000***	0.000***	0.041**	0.263	0.000***
EquityIRFMax SV	Spearman's ρ	0.273	0.884	-0.390	-0.223	0.589
	P value	0.007***	0.000***	0.000***	0.029**	0.000***
CDSIRFPrd SV	Spearman's ρ	-0.109	-0.065	0.132	0.116	-0.237
	P value	0.291	0.525	0.201	0.259	0.020**
EquityIRFPrd SV	Spearman's ρ	0.034	-0.198	0.156	0.430	-0.083
	P value	0.740	0.053*	0.130	0.000***	0.421
DiDe SV	Spearman's ρ	0.042	0.718	-0.374	-0.053	0.623
	P value	0.682	0.000***	0.000***	0.611	0.000***
LRMES	Spearman's ρ	0.182	0.686	-0.317	0.059	0.608
	P value	0.077*	0.000***	0.002***	0.565	0.000***
SRISK	Spearman's ρ	0.440	0.585	-0.084	0.329	0.667
	P value	0.000***	0.000***	0.417	0.001***	0.000***

(continued)

		EquityIRFMax SI	CDSIRFPrd SI	EquityIRFPrd SI	DiDe SI	ΔCoRisk SV
EquityIRFMax SI	Spearman's ρ	1.000				
	P value	1.000				
CDSIRFPrd SI	Spearman's ρ	0.110	1.000			
	P value	0.284	1.000			
EquityIRFPrd SI	Spearman's ρ	0.211	0.104	1.000		
	P value	0.039**	0.311	1.000		
DiDe SI	Spearman's ρ	0.774	0.075	0.175	1.000	
	P value	0.000***	0.467	0.088*	1.000	
ΔCoRisk SV	Spearman's ρ	0.253	0.175	-0.231	-0.054	1.000
	P value	0.013**	0.089*	0.024**	0.603	1.000
ΔCoVaR SV	Spearman's ρ	0.721	0.269	0.170	0.478	0.280
	P value	0.000***	0.008***	0.097*	0.000***	0.006***
CDSGranger SV	Spearman's ρ	0.560	0.011	0.378	0.361	0.233
	P value	0.000***	0.914	0.000***	0.000***	0.022**
EquityGranger SV	Spearman's ρ	0.383	0.072	0.635	0.388	-0.276
	P value	0.000***	0.484	0.000***	0.000***	0.006***
CDSIRFMax SV	Spearman's ρ	0.607	-0.006	-0.001	0.482	0.379
	P value	0.000***	0.952	0.994	0.000***	0.000***
EquityIRFMax SV	Spearman's ρ	0.894	0.078	0.300	0.830	0.094
	P value	0.000***	0.452	0.003***	0.000***	0.362
CDSIRFPrd SV	Spearman's ρ	-0.099	0.642	0.010	-0.036	0.163
	P value	0.335	0.000***	0.924	0.724	0.112
EquityIRFPrd SV	Spearman's ρ	-0.131	-0.114	-0.018	-0.222	0.232
	P value	0.205	0.270	0.859	0.030**	0.023**
DiDe SV	Spearman's ρ	0.698	0.169	0.167	0.300	0.311
	P value	0.000***	0.100	0.104	0.003***	0.002***
LRMES	Spearman's ρ	0.656	0.301	0.086	0.391	0.373
	P value	0.000***	0.003***	0.405	0.000***	0.000***
SRISK	Spearman's ρ	0.583	0.177	-0.112	0.308	0.446
	P value	0.000***	0.084*	0.276	0.002***	0.000***

(continued)

		ΔCoVaR SV	CDSGranger SV	EquityGranger SV	CDSIRFMax SV	EquityIRFMax SV
ΔCoVaR SV	Spearman's ρ	1.000				
	P value	1.000				
CDSGranger SV	Spearman's ρ	0.611	1.000			
	P value	0.000***	1.000			
EquityGranger SV	Spearman's ρ	0.321	0.482	1.000		
	P value	0.001***	0.000***	1.000		
CDSIRFMax SV	Spearman's ρ	0.612	0.750	0.042	1.000	
	P value	0.000***	0.000***	0.684	1.000	
EquityIRFMax SV	Spearman's ρ	0.668	0.542	0.521	0.541	1.000
	P value	0.000***	0.000***	0.000***	0.000***	1.000
CDSIRFPrd SV	Spearman's ρ	-0.099	-0.295	-0.117	-0.225	-0.159
	P value	0.336	0.004***	0.258	0.028**	0.122
EquityIRFPrd SV	Spearman's	-0.220	-0.123	-0.213	-0.060	-0.082
	P value	0.032**	0.233	0.037**	0.559	0.428
DiDe SV	Spearman's	0.899	0.588	0.281	0.530	0.602
	P value	0.000***	0.000***	0.006***	0.000***	0.000***
LRMES	Spearman's	0.934	0.516	0.174	0.571	0.579
	P value	0.000***	0.000***	0.090*	0.000***	0.000***
SRISK	Spearman's	0.708	0.392	-0.094	0.630	0.462
	P value	0.000***	0.000***	0.363	0.000***	0.000***

(continued)

		CDSIRFPrd SV	EquityIRFPrd SV	DiDe SV	LRMES	SRISK
CDSIRFPrd SV	Spearman's	1.000				
	P value	1.000				
EquityIRFPrd SV	Spearman's	0.074	1.000			
	P value	0.471	1.000			
DiDe SV	Spearman's	-0.132	-0.099	1.000		
	P value	0.201	0.336	1.000		
LRMES	Spearman's	-0.047	-0.088	0.850	1.000	
	P value	0.652	0.392	0.000***	1.000	
SRISK	Spearman's	-0.004	0.070	0.694	0.757	1.000
	P value	0.969	0.499	0.000***	0.000***	1.000

Appendix 80 Rank Correlations across Time by Systemic Risk Measures

		ΔCoRisk SI			ΔCoVaR SI			CDSGranger SI			EquityGranger SI		
		pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis
pre-crisis	Spearman's	1.000			1.000			1.000			1.000		
	P value	1.000			1.000			1.000			1.000		
crisis	Spearman's	0.058	1.000		0.622	1.000		0.101	1.000		0.720	1.000	
	P value	0.574	1.000		0.000***	1.000		0.328	1.000		0.000***	1.000	
post-crisis	Spearman's	0.156	0.730	1.000	0.707	0.764	1.000	-0.133	0.490	1.000	0.762	0.778	1.000
	P value	0.129	0.000***	1.000	0.000***	0.000***	1.000	0.196	0.000***	1.000	0.000***	0.000***	1.000

(continued)

		CDSIRFMax SI			EquityIRFMax SI			CDSIRFPrd SI			EquityIRFPrd SI		
		pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis
pre-crisis	Spearman's	1.000			1.000			1.000			1.000		
	P value	1.000			1.000			1.000			1.000		
crisis	Spearman's	0.563	1.000		0.327	1.000		-0.204	1.000		0.232	1.000	
	P value	0.000***	1.000		0.001***	1.000		0.046**	1.000		0.023**	1.000	
post-crisis	Spearman's	0.569	0.827	1.000	0.404	0.583	1.000	-0.259	-0.049	1.000	-0.059	0.352	1.000
	P value	0.000***	0.000***	1.000	0.000***	0.000***	1.000	0.011**	0.636	1.000	0.570	0.000***	1.000

(continued)

		DiDe SI			ΔCoRisk SV			ΔCoVaR SV			CDSGranger SV		
		pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis
pre-crisis	Spearman's	1.000			1.000			1.000			1.000		
	P value	1.000			1.000			1.000			1.000		
crisis	Spearman's	0.762	1.000		0.675	1.000		0.613	1.000		0.447	1.000	
	P value	0.000***	1.000		0.000***	1.000		0.000***	1.000		0.000***	1.000	
post-crisis	Spearman's	0.739	0.886	1.000	0.806	0.713	1.000	0.750	0.870	1.000	0.486	0.601	1.000
	P value	0.000***	0.000***	1.000	0.000***	0.000***	1.000	0.000***	0.000***	1.000	0.000***	0.000***	1.000

(continued)

		EquityGranger SV			CDSIRFMax SV			EquityIRFMax SV			CDSIRFPrd SV		
		pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis
pre-crisis	Spearman's	1.000			1.000			1.000			1.000		
	P value	1.000			1.000			1.000			1.000		
crisis	Spearman's	0.691	1.000		0.438	1.000		0.570	1.000		-0.067	1.000	
	P value	0.000***	1.000		0.000***	1.000		0.000***	1.000		0.517	1.000	
post-crisis	Spearman's	0.597	0.767	1.000	0.569	0.789	1.000	0.510	0.755	1.000	-0.017	-0.146	1.000
	P value	0.000***	0.000***	1.000	0.000***	0.000***	1.000	0.000***	0.000***	1.000	0.866	0.155	1.000

(continued)

		EquityIRFPrd SV			DiDe SV			LRMES			SRISK		
		pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis	pre-crisis	crisis	post-crisis
pre-crisis	Spearman's	1.000			1.000			1.000			1.000		
	P value	1.000			1.000			1.000			1.000		
crisis	Spearman's	0.266	1.000		0.687	1.000		0.557	1.000		0.854	1.000	
	P value	0.009***	1.000		0.000***	1.000		0.000***	1.000		0.000***	1.000	
post-crisis	Spearman's	0.096	0.233	1.000	0.676	0.865	1.000	0.655	0.832	1.000	0.873	0.978	1.000
	P value	0.354	0.022**	1.000	0.000***	0.000***	1.000	0.000***	0.000***	1.000	0.000***	0.000***	1.000

Appendix 81 Systemic Important Companies Ranked by ΔCoRisk

2007 Q3	2007 Q4	2008 Q1	2008 Q2	2008 Q3	2008 Q4	2009 Q1	2009 Q2
Macquarie Group	JPMorgan Chase & Co.	Japan Tobacco	Credit Suisse	Goldman Sachs	ICICI Bank	Munich Re Group	Deutsche Telekom
Shinhan Bank	Munich Re Group	Merck & Co.	BNP Paribas	Morgan Stanley	BASF SE	Allianz SE	Goldman Sachs
Aegon N.V.	Bank of America	Chubb Limited	Walt Disney	Deutsche Bank	Allstate	JPMorgan Chase & Co.	Altria Group
Hannover Re SE	Deutsche Bank	The Travelers Co.	Munich Re Group	Credit Suisse	BNP Paribas	Deutsche Telekom AG	Vodafone Group
Commerzbank AG	Allianz SE	Allianz SE	Deutsche Bank	Banco Santander	Intesa Sanpaolo	Wells Fargo & Co.	BNP Paribas
Sanofi S.A.	Credit Suisse Group	Munich Re Group	Societe Generale	Intesa Sanpaolo	Banco Santander	AXA	Bank of America
Allianz SE	Intesa Sanpaolo	Loews Corporation	Allianz SE	Barclays	Chubb Limited	Hannover Re SE	Allianz SE
JPMorgan Chase & Co.	HSBC Holdings	Deutsche Bank	The Travelers Co.	UniCredit	Munich Re Group	Assicurazioni Generali	Japan Tobacco
RBS	Morgan Stanley	JPMorgan Chase & Co.	ANZ	Lloyds Banking	Deutsche Bank	HSBC Holdings	HSBC Holdings
UBS AG	Goldman Sachs	Societe Generale	Honeywell	AIG	KB Kookmin Bank	Intesa Sanpaolo	JPMorgan Chase & Co.
BNP Paribas	UBS AG	BNP Paribas	Hannover Re SE	ANZ	Allianz SE	BNP Paribas	Deutsche Bank
Societe Generale	MGIC	Cisco Systems Inc.	BASF SE	BNP Paribas	AON Plc	Aviva Plc	Hannover Re SE
Munich Re Group	BNP Paribas	MetLife	Chubb Limited	Societe Generale	Loews Corporation	Scor SE	Banco Santander
American Express	Banco Santander	Credit Suisse Group	Intesa Sanpaolo	Commerzbank AG	Walt Disney	AT&T Inc.	ICICI Bank
Barclays	Bayer AG	Intesa Sanpaolo	Credit Agricole	UBS AG	The Hartford	Banco Santander	BMW
Chubb Limited	Assicurazioni Generali	Banco Santander	Goldman Sachs	Citigroup	Deutsche Telekom AG	Walt Disney	Nordea Bank
Banco Santander	Barclays	Assicurazioni Generali	Vodafone Group	National Australia Bank	Unum Group	Vodafone Group	PepsiCo, Inc.
AXA	Citigroup Inc.	CNA Financial	AXA	JPMorgan Chase & Co.	Lincoln National	UniCredit	Intesa Sanpaolo
HSBC Holdings	AXA	Allstate	McDonald	Standard Chartered	UniCredit	Bank of America	Walt Disney
ICICI Bank	Coca-Cola	The Hartford	Banco Santander	Nordea Bank	LVMH	BASF SE	UniCredit

Appendix 82 Systemic Vulnerable Companies Ranked by ΔCoRisk

2007 Q3	2007 Q4	2008 Q1	2008 Q2	2008 Q3	2008 Q4	2009 Q1	2009 Q2
QBE Insurance	American Express	Capital One	Old Mutual Plc	Old Mutual Plc	AIG	Old Mutual Plc	Old Mutual Plc
Intesa Sanpaolo	AstraZeneca Plc	AIG	Nordea Bank	Macquarie Group	Macquarie Group	Prudential Plc	Lincoln National
AXA	AIG	Citigroup	Macquarie Group	The Hartford	The Hartford	Lincoln National	AIG
BP Plc	QBE Insurance	American Express	Pfizer Inc.	Lincoln National	Old Mutual Plc	Legal & General	Legal & General
Toyota Motor	Citigroup Inc.	BP Plc	AIG	QBE Insurance	MetLife	The Hartford	The Hartford
Standard Chartered	BP Plc	Lincoln National	Lincoln National	Aegon N.V.	Prudential Plc	Macquarie Group	Macquarie Group
AstraZeneca Plc	The Home Depot	RBS	QBE Insurance	MetLife	Aegon N.V.	MetLife	Prudential Plc
Medtronic	Prudential Plc	Legal & General	Merck & Co.	UBS AG	Lincoln National	AIG	MetLife
The Hartford	Legal & General	Aviva Plc	The Hartford	Prudential Plc	UBS AG	Aegon N.V.	Citigroup
UniCredit	Aviva Plc	MBIA	Citigroup Inc.	AIG	Shinhan Bank	AstraZeneca Plc	BMW
Assicurazioni Generali	Pfizer Inc.	AstraZeneca Plc	Aegon N.V.	Citigroup Inc.	Legal & General	Medtronic	QBE Insurance
KBC Bank	Lincoln National	Aegon N.V.	UBS AG	Cathay Financial	QBE Insurance	Johnson & Johnson	Medtronic
HSBC Holdings	Nestle S.A.	Macquarie Group	American Express	Legal & General	Citigroup Inc.	Eli Lilly	AstraZeneca Plc
Societe Generale	Old Mutual Plc	KB Kookmin Bank	Prudential Plc	BP Plc	American Express	Shinhan Bank	Aegon N.V.
National Australia Bank	Lloyds Banking	Prudential Plc	MetLife	Shinhan Bank	BP Plc	QBE Insurance	UBS AG
Bank of America	Aegon N.V.	QBE Insurance	AT&T Inc.	Nestle S.A.	KB Kookmin Bank	UBS AG	Shinhan Bank
Berkshire Hathaway	Radian Group Inc.	UBS AG	BP Plc	Pfizer Inc.	Cathay Financial	BP Plc	Allstate
BNP Paribas	ANZ	Nestle S.A.	Amgen Inc	KB Kookmin Bank	RBS	BMW	RBS
Aviva Plc	MetLife	Pfizer Inc.	Legal & General	AT&T Inc.	Johnson & Johnson	KB Kookmin Bank	Eli Lilly
Aegon N.V.	RBS	Wells Fargo & Co.	Japan Tobacco	Merck & Co.	Nestle S.A.	LVMH	3M

Appendix 83 Systemic Important Companies Ranked by ΔCoVaR

2007 Q3	2007 Q4	2008 Q1	2008 Q2	2008 Q3	2008 Q4	2009 Q1	2009 Q2
Prudential Plc	Pfizer Inc.	Intesa Sanpaolo	Lincoln National	UBS AG	Loews Corporation	MetLife	3M
UniCredit	Bank of America	Loews Corporation	Allianz SE	AT&T Inc.	Banco Santander	Banco Santander	Unum Group
Old Mutual Plc	The Home Depot	KBC Bank	Deutsche Bank	Morgan Stanley	BASF SE	Societe Generale	UBS AG
ING Group	Allianz SE	Prudential Plc	Citigroup Inc.	JPMorgan Chase & Co.	CNA Financial	3M	AXA
Societe Generale	Citigroup Inc.	The Hartford	HSBC Holdings	chubb Limited	Pfizer Inc.	Unum Group	Allianz SE
AstraZeneca Plc	KBC Bank	Banco Santander	MGIC	American Express	Morgan Stanley	Loews Corporation	UniCredit
The Hartford	AIG	Coca-Cola	BMW	Deutsche Telekom AG	American Financial	Honeywell	MetLife
MetLife	Aviva Plc	American Financial	Pfizer Inc.	Goldman Sachs	Intesa Sanpaolo	chubb Limited	Deutsche Bank
Banco Santander	ING Group	MetLife	AT&T Inc.	Allianz SE	Procter & Gamble Co.	Intesa Sanpaolo	Loews Corporation
Exxon Mobil Corp.	American Express	Lincoln National	American Express	Nordea Bank	American Express	Exxon Mobil Corp.	The Hartford
Sanofi S.A.	Morgan Stanley	Deutsche Bank	Banco Santander	Citigroup Inc.	AIG	UBS AG	Standard Chartered
AXA	Lloyds Banking	AXA	LVMH	Cisco Systems Inc.	Assicurazioni Generali	Lloyds Banking	Cisco Systems
Loews Corporation	Wells Fargo & Co.	Commerzbank AG	Legal & General	Honeywell	The Travelers Co。	Old Mutual Plc	Total S.A.
AIG	MetLife	Unum Group	Unum Group	The Hartford	Aetna Inc.	American Express	Honeywell
Credit Suisse	JPMorgan Chase & Co.	Aviva Plc	Cisco Systems	RBS	HSBC Holdings	CNA Financial	Commerzbank AG
Aviva Plc	Barclays	ING Group	Wells Fargo & Co.	Aegon N.V.	Merck & Co.	Allianz SE	Banco Santander
Assicurazioni Generali	Prudential Plc	Sanofi S.A.	Commerzbank AG	Banco Santander	Citigroup	Cisco Systems Inc.	American Financial
Lincoln National	Credit Agricole	AIG	Bank of America	Cigna Corporation	UniCredit	Assicurazioni Generali	MBIA
Lloyds Banking	Goldman Sachs	Citigroup Inc.	Allstate	ING Group	Total S.A.	The Hartford	BMW
Allianz SE	Old Mutual Plc	BNP Paribas	JPMorgan Chase&Co.	Lincoln National	Eli Lilly and Company	UniCredit	Morgan Stanley

Appendix 84 Systemic Vulnerable Companies Ranked by ΔCoVaR

2007 Q3	2007 Q4	2008 Q1	2008 Q2	2008 Q3	2008 Q4	2009 Q1	2009 Q2
Radian Group	Radian Group	MBIA	MBIA	AIG	Morgan Stanley	Lincoln National	The Hartford
MGIC	MGIC	Radian Group	MGIC	Radian Group	The Hartford	Citigroup	MGIC
MBIA	MBIA	UBS AG	Radian Group Inc.	MGIC	Lincoln National	The Hartford	Capital One
Old Mutual Plc	Capital One	MGIC	Citigroup	Bank of America	Radian Group	Bank of America	Radian Group
Prudential Plc	Morgan Stanley	Citigroup Inc.	Morgan Stanley	MBIA	Citigroup Inc.	Radian Group Inc.	MBIA
Barclays	RBS	RBS	UBS AG	RBS	ING Group	MGIC	Lincoln National
Legal & General	Goldman Sachs	Commerzbank AG	Capital One	Citigroup Inc.	MGIC	MetLife	Bank of America
Lincoln National	Citigroup Inc.	Capital One	RBS	UBS AG	AIG	MBIA	AIG
Standard Chartered	Barclays	Morgan Stanley	Commerzbank AG	Morgan Stanley	MetLife	Wells Fargo & Co.	CNA Financial
Societe Generale	AIG	Credit Agricole	AIG	JPMorgan Chase & Co.	Bank of America	Lloyds Banking	KBC Bank
AXA	Prudential Plc	Barclays	Barclays	Credit Agricole	MBIA	RBS	Aegon N.V.
RBS	JPMorgan Chase & Co.	Old Mutual Plc	American Express	Capital One	Unum Group	Capital One	Wells Fargo & Co.
BNP Paribas	American Express	AXA	JPMorgan Chase & Co.	Wells Fargo & Co.	Cigna Corporation	Aegon N.V.	MetLife
Morgan Stanley	Old Mutual Plc	ING Group	Bank of America	Barclays	Deutsche Bank	Morgan Stanley	ING Group
Commerzbank AG	Bank of America	Credit Suisse Group	Standard Chartered	Prudential Plc	Credit Suisse	JPMorgan Chase & Co.	RBS
MetLife	Lloyds Banking	AIG	Wells Fargo & Co.	AXA	CNA Financial	ING Group	American Express
Aviva Plc	Wells Fargo & Co.	BNP Paribas	Prudential Plc	Aegon N.V.	American Financial	Unum Group	Unum Group
Goldman Sachs	UBS AG	Prudential Plc	Goldman Sachs	Goldman Sachs	Goldman Sachs	Barclays	Deutsche Bank
UniCredit	Standard Chartered	Aegon N.V.	Lloyds Banking	Aviva Plc	Allstate	CNA Financial	Barclays
American Express	Commerzbank AG	CNA Financial	Lincoln National	Lincoln National	Prudential Plc	Old Mutual Plc	Commerzbank AG

Appendix 85 Risky Companies Ranked by the Maximum Values of CDS-Based IRF

Impulse			Response		
2007	2008	2009	2007	2008	2009
AXA	Morgan Stanley	Morgan Stanley	RBS	Credit Agricole	Intesa Sanpaolo
Assicurazioni Generali	Chubb Limited	Goldman Sachs	AXA	Intesa Sanpaolo	Aegon N.V.
Capital One	The Hartford	Societe Generale	Deutsche Bank	Barclays	UniCredit
Aviva Plc	The Travelers Co.	Munich Re Group	Vodafone	Nestle S.A.	AXA
HSBC	AXA	Citigroup Inc.	BNP Paribas	RBS	Banco Santander
Allianz SE	Allianz SE	Credit Agricole	Hannover Re SE	Bayer AG	BMW
Citigroup Inc.	Walmart	Assicurazioni Generali	BMW	Allianz SE	Credit Suisse
BNP Paribas	Allstate	MetLife	Banco Santander	Munich Re Group	Hannover Re SE
Commerzbank AG	MetLife	Aviva Plc	Barclays	Societe Generale	RBS
Bank of America	American Express	UBS AG	Credit Suisse	Credit Suisse	Allianz SE
Munich Re Group	Cigna Corporation	Intesa Sanpaolo	Deutsche Telekom AG	Vodafone Group	Assicurazioni Generali
Deutsche Bank	Lincoln National	Hannover Re SE	Intesa Sanpaolo	Sanofi S.A.	Morgan Stanley
Banco Santander	Scor SE	Banco Santander	HSBC Holdings	Assicurazioni Generali	Barclays
UniCredit	Aviva Plc	Lloyds Banking Group	Bayer AG	ING Group	Credit Agricole
Credit Suisse	Assicurazioni Generali	American Express	LVMH	BMW	UBS AG
Intesa Sanpaolo	AIG	Standard Chartered	Allstate	UBS AG	Standard Chartered
JPMorgan Chase & Co.	Hannover Re SE	BNP Paribas	The Travelers Co。	BNP Paribas	Societe Generale
UBS AG	BNP Paribas	Commerzbank AG	UBS AG	LVMH	Capital One
Bayer AG	Lloyds Banking	BMW	Allianz SE	UniCredit	American Express
Hannover Re SE	ING Group	Allianz SE	UniCredit	Deutsche Telekom AG	BNP Paribas

Appendix 86 Risky Companies Ranked by the Maximum Values of Equity-Based IRF

Impulse			Response		
2007	2008	2009	2007	2008	2009
JPMorgan Chase & Co.	The Hartford	Amgen Inc	Deutsche Bank	Deutsche Bank	UniCredit
Goldman Sachs	Morgan Stanley	Bank of America	Exxon Mobil Corp.	UBS AG	JPMorgan Chase & Co.
American Express	Honeywell	American Financial	Pfizer Inc.	Munich Re Group	Lincoln National
Citigroup	CNA Financial	Morgan Stanley	Goldman Sachs	Goldman Sachs	MetLife
Deutsche Bank	Cisco Systems Inc.	Allstate	Allianz SE	Allianz SE	Goldman Sachs
Commerzbank AG	Goldman Sachs	BASF SE	Banco Santander	Citigroup Inc.	Unum Group
Morgan Stanley	Citigroup Inc.	Allianz SE	Credit Suisse	Lincoln National	Honeywell
MetLife	Allstate	CNA Financial	MetLife	Hannover Re SE	Aegon N.V.
American Financial	MetLife	Deutsche Bank	AT&T Inc.	Pfizer Inc.	The Hartford
Exxon Mobil	3M	Citigroup	UBS AG	Bank of America	ING Group
The Hartford	UBS AG	MetLife	Munich Re Group	Cisco Systems Inc.	Loews Corporation
The Home Depot	Bank of America	The Travelers Co.	Bank of America	Morgan Stanley	HSBC Holdings
AIG	Lincoln National Corp.	Wells Fargo & Co.	The Hartford	Capital One	Wells Fargo & Co.
Bank of America	AT&T Inc.	The Hartford	Coca-Cola	Walt Disney	Allstate
Lincoln National	Deutsche Bank	UBS AG	Hannover Re SE	AT&T Inc.	Cisco Systems Inc.
Walmart	Deutsche Telekom AG	Marsh & McLennan Co.	Lincoln National	ING Group	Walt Disney
Altria Group Inc.	The Travelers Co.	Aegon N.V.	JPMorgan Chase & Co.	The Travelers Co.	Allianz SE
Old Mutual Plc	Eli Lilly and Company	BNP Paribas	American Express	American Express	CNA Financial
Loews Corporation	Procter & Gamble Co.	Loews Corporation	AIG	MetLife	Credit Suisse
Macquarie Group	Pfizer Inc.	American Express	Standard Chartered	Banco Santander	AXA

Appendix 87 Risky Companies Ranked by the Lasting Periods of CDS-Based IRF

Impulse			Response		
2007	2008	2009	2007	2008	2009
Radian Group	AT&T Inc.	AIG	Prudential Plc	KB Kookmin Bank	Aetna Inc.
MGIC	JPMorgan Chase & Co.	Aetna Inc.	Radian Group	QBE Insurance	American Financial
Cathay Financial	Credit Suisse	Cigna Corporation	ING Group	JPMorgan Chase & Co.	AIG
KBC Bank	AIG	Intesa Sanpaolo	ANZ	Banco Santander	Cigna Corporation
Prudential Plc	MetLife	Wells Fargo & Co.	MGIC	Toyota Motor	Prudential Plc
ING Group	Lincoln National	Aegon N.V.	Sanofi S.A.	MetLife	RBS
Sanofi S.A.	Bank of America	Prudential Plc	Lloyds Banking	Macquarie Group	Aegon N.V.
ANZ	MGIC	Citigroup	AT&T Inc.	Lincoln National	KB Kookmin Bank
Wells Fargo & Co.	Aetna Inc.	McDonald	Assicurazioni Generali	American Financial	Exxon Mobil
Legal & General	Wells Fargo & Co.	Aviva Plc	HSBC	Shinhan Bank	Macquarie Group
AT&T Inc.	KB Kookmin Bank	RBS	Cathay Financial	Nordea Bank	QBE Insurance
Bank of America	McDonald	Deutsche Telekom AG	KBC Bank	Credit Agricole	Legal & General
Old Mutual Plc	PepsiCo, Inc.	Lincoln National	Commerzbank AG	Bank of America	Intesa Sanpaolo
Citigroup Inc.	Goldman Sachs	3M	Legal & General	Credit Suisse	Wells Fargo & Co.
Assicurazioni Generali	Radian Group	American Financial	Macquarie Group	AIG	Deutsche Telekom AG
Scor SE	Deutsche Bank	Merck & Co.	Wells Fargo & Co.	Morgan Stanley	Aviva Plc
Deutsche Bank	Prudential Plc	American Express	McDonald	Walt Disney	Merck & Co.
Barclays	BMW	AXA	Munich Re Group	Honeywell	Sanofi S.A.
The Home Depot	Honeywell	UBS AG	QBE Insurance	MGIC	3M
Allianz SE	Unum Group	Walt Disney	Intesa Sanpaolo	Goldman Sachs	AXA

Appendix 88 Risky Companies Ranked by the Lasting Periods of Equity-Based IRF

Impulse			Response		
2007	2008	2009	2007	2008	2009
MGIC	Capital One	Amgen Inc	Macquarie Group	Nestle S.A.	Shinhan Bank
American Financial	Nestle S.A.	Credit Suisse	National Australia Bank	ANZ	KB Kookmin Bank
Radian Group	Altria Group	UniCredit	ICICI Bank	Altria Group	UniCredit
Wells Fargo & Co.	AT&T Inc.	AIG	KB Kookmin Bank	KBC Bank	ANZ
Walt Disney	American Express	Aetna Inc.	Toyota Motor	Scor SE	Japan Tobacco
Aetna Inc.	Walt Disney	Deutsche Bank	Walt Disney	Aetna Inc.	Macquarie Group
Capital One	Lincoln National	Eli Lilly and Co.	Wells Fargo & Co.	MetLife	PepsiCo, Inc.
Johnson & Johnson	Loews Corporation	Munich Re Group	Shinhan Bank	Japan Tobacco	Commerzbank AG
American Express	Pfizer Inc.	Wells Fargo & Co.	Nestle S.A.	Amgen Inc	Toyota Motor
Citigroup Inc.	Bank of America	Hannover Re SE	QBE Insurance	Legal & General	Assicurazioni Generali
Exxon Mobil	KBC Bank	CNA Financial	Aetna Inc.	Pfizer Inc.	Aetna Inc.
Coca-Cola	AON Plc	Intesa Sanpaolo	Aviva Plc	Marsh & McLennan	QBE Insurance
Loews Corporation	Unum Group	PepsiCo, Inc.	Total S.A.	Shinhan Bank	Goldman Sachs
Lincoln National	Exxon Mobil	Johnson & Johnson	Cathay Financial	LVMH	CNA Financial
AT&T Inc.	Berkshire Hathaway	MetLife	Assicurazioni Generali	Lincoln National	JPMorgan Chase & Co.
MetLife	Aetna Inc.	Commerzbank AG	Japan Tobacco	Walt Disney	Vodafone
Macquarie Group	McDonald	Loews Corporation	Bank of America	National Australia Bank	AON Plc
The Hartford	Goldman Sachs	The Hartford	American Financial	The Travelers Co.	Barclays
Marsh & McLennan	Citigroup Inc.	UBS AG	Legal & General	ICICI Bank	ING Group
AIG	The Travelers Companies	Goldman Sachs	The Hartford	AON Plc	Deutsche Telekom AG

Appendix 89 Systemic Important Companies Ranked by DiDe

2007 Q3	2007 Q4	2008 Q1	2008 Q2	2008 Q3	2008 Q4	2009 Q1	2009 Q2
BNP Paribas	Loews Corporation	Honeywell	Loews Corporation	Honeywell	BNP Paribas	Deutsche Bank	Loews Corporation
3M	Nordea Bank	Loews Corporation	Allianz SE	Loews Corporation	Loews Corporation	Loews Corporation	Allianz SE
Allianz SE	BNP Paribas	Allianz SE	Honeywell	Allianz SE	Credit Agricole	BNP Paribas	BNP Paribas
Loews Corporation	Honeywell	3M	BNP Paribas	BNP Paribas	Banco Santander	Allianz SE	ING Group
Deutsche Bank	3M	Deutsche Bank	Walt Disney	Walt Disney	Deutsche Bank	Honeywell	Deutsche Bank
AXA	Deutsche Bank	BNP Paribas	3M	3M	Allianz SE	Walt Disney	Honeywell
Credit Agricole	Societe Generale	BASF SE	ING Group	BASF SE	Societe Generale	ING Group	3M
Societe Generale	Allstate	Walt Disney	Deutsche Bank	AXA	ING Group	Societe Generale	Banco Santander
Nordea Bank	The Hartford	Banco Santander	BASF SE	Intesa Sanpaolo	JPMorgan Chase & Co.	Credit Agricole	AXA
Exxon Mobil Corp.	Allianz SE	AXA	Intesa Sanpaolo	LVMH	Munich Re Group	3M	JPMorgan Chase & Co.
Lincoln National	ING Group	JPMorgan Chase & Co.	Nordea Bank	Deutsche Bank	Walt Disney	Banco Santander	Walt Disney
MetLife	Walt Disney	Nordea Bank	Banco Santander	Assicurazioni Generali	Bank of America	AXA	Munich Re Group
The Hartford	JPMorgan Chase & Co.	Allstate	AXA	Allstate	Honeywell	Munich Re Group	Intesa Sanpaolo
Allstate	MetLife	Societe Generale	JPMorgan Chase & Co.	Munich Re Group	Wells Fargo & Co.	Total S.A.	Societe Generale
Wells Fargo & Co.	Credit Agricole	ING Group	UniCredit	Banco Santander	Intesa Sanpaolo	Marsh & McLennan	Assicurazioni Generali
JPMorgan Chase & Co.	AXA	Bank of America	Total S.A.	Societe Generale	HSBC Holdings	JPMorgan Chase & Co.	chubb Limited
BASF SE	Banco Santander	Intesa Sanpaolo	Exxon Mobil Corp.	Credit Agricole	AXA	BASF SE	Credit Suisse
Honeywell	Lincoln National C	Assicurazioni Generali	Societe Generale	chubb Limited	Commerzbank AG	Intesa Sanpaolo	LVMH
Banco Santander	Bank of America	Exxon Mobil Corp.	Allstate	Nordea Bank	Marsh & McLennan	Exxon Mobil Corp.	BASF SE
Bank of America	BASF SE	Credit Agricole	Johnson & Johnson	JPMorgan Chase & Co.	UniCredit	chubb Limited	Credit Agricole

Appendix 90 Systemic Vulnerable Companies Ranked by DiDe

2007 Q3	2007 Q4	2008 Q1	2008 Q2	2008 Q3	2008 Q4	2009 Q1	2009 Q2
Radian Group	Radian Group	Radian Group	Radian Group	Radian Group	Radian Group	Lincoln National	AIG
MGIC	MBIA	MBIA	MBIA	AIG	Old Mutual Plc	AIG	Radian Group
MBIA	Capital One	MGIC	MGIC	MBIA	MBIA	Old Mutual Plc	MBIA
KBC Bank	MGIC	Capital One	Capital One	Morgan Stanley	Lincoln National	Radian Group	Old Mutual Plc
Capital One	Morgan Stanley	Unum Group	Morgan Stanley	MGIC	MGIC	MBIA	MGIC
Unum Group	American Express	Aegon N.V.	Lincoln National	MetLife	The Hartford	MGIC	Lincoln National
Morgan Stanley	AXA	Morgan Stanley	American Express	Goldman Sachs	Prudential Plc	The Hartford	The Hartford
ING Group	KBC Bank	Lincoln National	Unum Group	Capital One	MetLife	MetLife	MetLife
CNA Financial	Citigroup	American Express	AIG	American Express	Aegon N.V.	Legal & General	Citigroup
The Home Depot	CNA Financial	Old Mutual Plc	AXA	Aegon N.V.	AIG	American Express	Legal & General
Goldman Sachs	The Home Depot	Citigroup	Aegon N.V.	The Hartford	Morgan Stanley	Citigroup Inc.	CNA Financial
American Express	Unum Group	MetLife	Citigroup Inc.	Citigroup Inc.	Legal & General	Prudential Plc	Unum Group
Deutsche Bank	Allianz SE	AXA	MetLife	Lincoln National	CNA Financial	Aegon N.V.	Prudential Plc
AXA	Lincoln National	ING Group	Deutsche Bank	UBS AG	BMW	Unum Group	KBC Bank
Banco Santander	Goldman Sachs	The Hartford	Goldman Sachs	Barclays	American Express	Aviva Plc	American Express
JPMorgan Chase & Co.	Aegon N.V.	The Home Depot	Old Mutual Plc	RBS	Unum Group	Morgan Stanley	Aegon N.V.
Commerzbank AG	Deutsche Bank	Goldman Sachs	CNA Financial	Macquarie Group	Goldman Sachs	Bank of America	Bank of America
American Financial	ING Group	AIG	The Hartford	Old Mutual Plc	AXA	CNA Financial	Morgan Stanley
Lincoln National	Banco Santander	Aviva Plc	Aviva Plc	Deutsche Bank	ICICI Bank	Capital One	Aviva Plc
Allianz SE	Aviva Plc	UBS AG	Credit Agricole	ING Group	Berkshire Hathaway	Allstate	Capital One

Appendix 91 Risky Companies Ranked by LRMES

2007 Q3	2007 Q4	2008 Q1	2008 Q2	2008 Q3	2008 Q4	2009 Q1	2009 Q2
Radian Group	Radian Group	MBIA	MBIA	MGIC	Lincoln National	Lincoln National	Capital One
Macquarie Group	MGIC	Radian Group	MGIC	Radian Group	Morgan Stanley	Citigroup Inc.	The Hartford
MGIC	Capital One	RBS	Radian Group	AIG	Radian Group	The Hartford	MGIC
Prudential Plc	Morgan Stanley	Old Mutual Plc	Morgan Stanley	MBIA	MGIC	Bank of America	Radian Group
Cathay Financial	MBIA	Commerzbank AG	AIG	Bank of America	Citigroup	RBS	Lincoln National
Old Mutual Plc	RBS	MGIC	Citigroup	Citigroup	Unum Group	MBIA	MBIA
MBIA	Barclays	Barclays	Capital One	Capital One	Bank of America	MGIC	Bank of America
Legal & General	Goldman Sachs	Macquarie Group	American Express	JPMorgan Chase & Co.	The Hartford	Lloyds Banking	Wells Fargo & Co.
Barclays	Prudential Plc	Credit Suisse	Bank of America	Wells Fargo & Co.	Capital One	MetLife	KBC Bank
Standard Chartered	Old Mutual Plc	Aviva Plc	JPMorgan Chase & Co.	Morgan Stanley	AIG	Wells Fargo & Co.	CNA Financial
Morgan Stanley	Citigroup	Credit Agricole	Wells Fargo & Co.	American Express	MBIA	Aegon N.V.	American Express
Societe Generale	AIG	Standard Chartered	Commerzbank AG	Lincoln National	Prudential Plc	Radian Group	MetLife
American Express	American Express	Capital One	Macquarie Group	Goldman Sachs	Allstate	Barclays	Aegon N.V.
AXA	Standard Chartered	AXA	Goldman Sachs	The Hartford	ING Group	ING Group	AIG
BNP Paribas	JPMorgan Chase & Co.	ING Group	RBS	RBS	MetLife	Morgan Stanley	ING Group
Goldman Sachs	Wells Fargo & Co.	Societe Generale	Cisco Systems Inc.	MetLife	CNA Financial	Unum Group	JPMorgan Chase & Co.
Commerzbank AG	Lloyds Banking	Citigroup	Lincoln National	Barclays	Aegon N.V.	Capital One	RBS
RBS	Aviva Plc	Aegon N.V.	CNA Financial	Prudential Plc	American Financial	JPMorgan Chase & Co.	Unum Group
Lincoln National	The Hartford	Prudential Plc	Prudential Plc	Credit Agricole	Credit Suisse	Aviva Plc	Barclays
Aviva Plc	Legal & General	UBS AG	Credit Agricole	AXA	AXA	CNA Financial	Aviva Plc

Appendix 92 Risky Companies Ranked by SRISK

2007 Q3	2007 Q4	2008 Q1	2008 Q2	2008 Q3	2008 Q4	2009 Q1	2009 Q2
UBS AG	RBS	RBS	RBS	RBS	RBS	RBS	BNP Paribas
RBS	UBS AG	Deutsche Bank	UBS AG	Barclays	Barclays	BNP Paribas	RBS
Deutsche Bank	Deutsche Bank	UBS AG	Deutsche Bank	Deutsche Bank	Deutsche Bank	Deutsche Bank	Deutsche Bank
Barclays	Barclays	Barclays	Barclays	UBS AG	UBS AG	Barclays	Barclays
BNP Paribas	BNP Paribas	BNP Paribas	BNP Paribas	BNP Paribas	BNP Paribas	UBS AG	Credit Agricole
Credit Agricole	Credit Agricole	Credit Agricole	Credit Agricole	Credit Agricole	HSBC Holdings	Credit Agricole	UBS AG
ING Group	ING Group	ING Group	ING Group	JPMorgan Chase & Co.	Credit Agricole	Bank of America	Bank of America
Societe Generale	Societe Generale	Citigroup	Citigroup	HSBC Holdings	JPMorgan Chase & Co.	HSBC Holdings	Citigroup Inc.
Morgan Stanley	Citigroup	HSBC Holdings	Societe Generale	ING Group	ING Group	JPMorgan Chase & Co.	JPMorgan Chase & Co.
Allianz SE	HSBC Holdings	Societe Generale	UniCredit	Citigroup	Citigroup	ING Group	ING Group
Citigroup Inc.	Morgan Stanley	Allianz SE	JPMorgan Chase & Co.	Bank of America	Bank of America	Citigroup Inc.	HSBC Holdings
Commerzbank AG	Commerzbank AG	UniCredit	Commerzbank AG	Societe Generale	Societe Generale	Societe Generale	Lloyds Banking
UniCredit	Goldman Sachs	Morgan Stanley	Allianz SE	UniCredit	UniCredit	Commerzbank AG	Societe Generale
Credit Suisse	UniCredit	JPMorgan Chase & Co.	Morgan Stanley	Allianz SE	Banco Santander	UniCredit	Commerzbank AG
Goldman Sachs	Allianz SE	Credit Suisse Group	Credit Suisse Group	Credit Suisse Group	Allianz SE	Banco Santander	Banco Santander
HSBC	Credit Suisse	Commerzbank AG	HSBC Holdings	AIG	Wells Fargo & Co.	Wells Fargo & Co.	UniCredit
AXA	JPMorgan Chase & Co.	Goldman Sachs	Goldman Sachs	Goldman Sachs	Credit Suisse	Lloyds Banking	Wells Fargo & Co.
Banco Santander	Legal & General	AXA	Bank of America	Morgan Stanley	Commerzbank AG	Credit Suisse	AIG
Legal & General	Aviva Plc	Bank of America	AXA	Banco Santander	AXA	Goldman Sachs	AXA
Aviva Plc	Lloyds Banking	Banco Santander	AIG	AXA	AIG	AXA	Credit Suisse

Appendix 93 Descriptive Statistics of the Minimmum and Maximum Values of the Risk Indicators

	Mean	Median	St.Dev.	Min	Max
MinEqtRet	-1.075651	-0.8633423	0.805088	-4.268334	-0.066888
MaxCDSRet	2.850908	2.74232	0.8126044	0.6607586	5.557914
Volatility	0.0155139	0.0149376	0.004645	0.0073336	0.0345387
VaR	0.0187648	0.01884	0.004556	0.0090638	0.0317672
ES	0.0279652	0.0274321	0.0073041	0.0132762	0.0506984
Beta	1.318694	1.315466	0.3402607	0.6187819	2.093292
CDSs	29.66045	22.65	22.42113	6.5	111.5
Z-Score	12.75689	14.69881	79.00055	-399.2046	208.2068
$\Delta CoRisk$SI	0.0985912	0.0766215	0.0856824	0.0309204	0.7033127
$\Delta CoRisk$SV	0.2527629	0.2270877	0.1267785	0.0718466	0.7033127
$\Delta CoVaR$SI	0.0120475	0.0117987	0.0036991	0.0038408	0.0215971
$\Delta CoVaR$SV	0.0114477	0.0107966	0.0039687	0.0029806	0.0215971
CDSIRFMaxSI	0.2758542	0.2646182	0.1413099	0.0975904	0.8343668
CDSIRFMaxSV	0.2747782	0.2314391	0.1400703	0.1189904	0.8343668
CDSIRFPrdSI	14.88542	14	3.846721	6	28
CDSIRFPrdSV	16.22917	16.5	3.579118	8	28
EqtIRFMaxSI	0.3806522	0.3579854	0.1412729	0.0818937	0.7224195
EqtIRFMaxSV	0.3828441	0.3634718	0.1386458	0.1279673	0.7224195
EqtIRFPrdSI	6.864583	7	1.833144	4	12
EqtIRFPrdSV	6.927083	7	1.778496	5	12
CDSGrangerSI	24.34375	24.5	11.43478	3	51
CDSGrangerSV	24.34733	23	12.54955	2	56
EqtGrangerSI	19	10.5	21.00476	1	85
EqtGrangerSV	17	14.5	11.56947	2	62
DiDeSI	0.0734229	0.0747267	0.0213249	0.0226266	0.1191687
DiDeSV	0.0771887	0.0687291	0.0319125	0.0296214	0.2122227
LRMES	0.2686578	0.264214	0.0732988	0.0802664	0.4265388
SRISK	-18292.75	-7821.45	67731	-282150.8	189039.4

MinEqtRet (MaxCDSRet) denotes the actual minimum equity returns (maximum CDS returns) during the period from 2007 Q3 to 2008 Q4. Risk measures are their maximum or minimum values during the period of 2006 Q1 to 2007Q2. VaR is the 95th percentile. CDSs is the CDS spread. the suffix of "SI" of the systemic risk measures means the systemic importance of the firms. the suffix of "SV" of the systemic risk measures means the systemic vulnerability of the firms. "~IRFMax~" refers to the IRF results based on the maximum values of the impulse response plots. "~IRFPrd~"refers to the IRF results based on the lasting periods in the impulse response plots.

Appendix 94 Descriptive Statistics of the Mean Values of the Risk Indicators

	Mean	Median	St.Dev.	Min	Max
MeanEqtRet	-0.2441237	-0.1685951	0.2570528	-1.646437	0.1210556
MeanCDSRet	1.740717	1.774005	0.6058145	-0.0037083	3.307681
Volatility	0.0119488	0.0117509	0.0028537	0.0063416	0.0211063
VaR	0.0187648	0.01884	0.004556	0.0090638	0.0317672
ES	0.0279652	0.0274321	0.0073041	0.0132762	0.0506984
Beta	1.000825	1.035391	0.3000251	0.239558	1.708932
CDSs	17.06761	13.9041	12.54685	3.729487	71.94615
Z-Score	55.1685	38.70661	59.88045	-53.33549	261.6606
$\Delta CoRisk$SI	0.0424798	0.0382638	0.0258665	0.0076891	0.2003157
$\Delta CoRisk$SV	0.0424798	0.0435086	0.011541	0.0107654	0.0723652
$\Delta CoVaR$SI	0.0049737	0.0051252	0.0017481	0.0001701	0.0091253
$\Delta CoVaR$SV	0.0049737	0.0048783	0.0018274	0.0001844	0.0093494
CDSIRFMaxSI	0.1387652	0.1319925	0.0447349	0.0695428	0.3456557
CDSIRFMaxSV	0.129276	0.1215543	0.0306545	0.0758633	0.2017168
CDSIRFPrdSI	8.817537	8.261364	1.896597	5.666667	17.41379
CDSIRFPrdSV	9.149281	8.891007	2.038382	5.78125	17.85714
EqtIRFMaxSI	0.2202912	0.223471	0.0728327	0.0500689	0.4274089
EqtIRFMaxSV	0.2087527	0.212859	0.0591054	0.0487931	0.38824
EqtIRFPrdSI	4.781257	4.666667	0.5387617	3.5	7
EqtIRFPrdSV	4.787825	4.741667	0.4255683	4.071429	6.5
CDSGrangerSI	24.34375	24.5	11.43478	3	51
CDSGrangerSV	24.34733	23	12.54955	2	56
EqtGrangerSI	19	10.5	21.00476	1	85
EqtGrangerSV	17	14.5	11.56947	2	62
DiDeSI	0.0664752	0.0688748	0.0193871	0.0215377	0.1050504
DiDeSV	0.0664752	0.0629012	0.024803	0.0214567	0.1808162
LRMES	0.2686578	0.264214	0.0732988	0.0802664	0.4265388
SRISK	-18292.75	-7821.45	67731	-282150.8	189039.4

MeanEqtRet (MeanCDSRet) denotes the actual mean equity returns (mean CDS returns) during the period from 2007 Q3 to 2008 Q4. Risk measures are their mean values during the period of 2006 Q1 to 2007Q2. VaR is the 95^{th} percentile. CDSs is the CDS spread. the suffix of “SI” of the systemic risk measures means the systemic importance of the firms. the suffix of “SV” of the systemic risk measures means the systemic vulnerability of the firms. “~IRFMax~” refers to the IRF results based on the maximum values of the impulse response plots. “~IRFPrd~”refers to the IRF results based on the lasting periods in the impulse response plots.

Appendix 95 Rank Correlation Matrix of the Minimum and Maximum Values of the Variables

	MinEqtRet	MaxCDSRet	MaxLeverage	Size	Illiquidity	Volatility	VaR
MinEqtRet	1						
MaxCDSRet	-0.5295	1					
	0.000***						
MaxLeverage	-0.6605	0.3958	1				
	0.000***	0.000***					
MaxMV	0.2972	-0.0364	-0.236	1			
	0.003***	0.7247	0.021**				
Illiquidity	-0.5484	0.4633	0.2809	-0.2695	1		
	0.000***	0.000***	0.006***	0.008***			
Volatility	-0.3018	0.0608	0.2643	-0.4349	0.0888	1	
	0.003***	0.5564	0.009***	0.000***	0.3897		
VaR	-0.2785	0.1173	0.3162	-0.4135	0.0119	0.8913	1
	0.006***	0.2552	0.002***	0.000***	0.9081	0.000***	
ES	-0.3232	0.0893	0.3025	-0.4004	0.0719	0.9359	0.8916
	0.001***	0.3871	0.0027	0.0001	0.4862	0	0
Beta	-0.4387	0.1916	0.4193	-0.2032	-0.0131	0.5522	0.6243
	0.000***	0.061*	0.000***	0.047**	0.8994	0.000***	0.000***
CDSs	-0.1335	-0.2607	-0.0456	-0.5389	0.0363	0.3441	0.2385
	0.1947	0.010**	0.659	0.000***	0.7251	0.001***	0.019**
Z-Score	0.2087	-0.0092	-0.2479	0.4144	-0.0479	-0.2641	-0.2478
	0.041**	0.9288	0.015**	0.000***	0.6432	0.009***	0.015**
$\Delta CoRisk$SI	0.265	-0.1738	-0.1747	0.4091	-0.1318	-0.2501	-0.1712
	0.009***	0.090*	0.089*	0.000***	0.2004	0.014**	0.095*
$\Delta CoRisk$SV	-0.2443	0.2652	0.3916	0.3304	0.0306	**0.0589**	0.0849
	0.016**	0.009***	0.000***	0.001***	0.7675	0.5688	0.411
$\Delta CoVaR$SI	-0.517	0.3948	0.6592	-0.0993	0.0433	0.2891	0.4478
	0.000***	0.000***	0.000***	0.3359	0.6755	0.004***	0.000***
$\Delta CoVaR$SV	-0.5207	0.346	0.6896	-0.2431	0.0667	**0.6135**	**0.7173**
	0.000***	0.001***	0.000***	0.017**	0.5182	0.000***	0.000***
CDSIRFMaxSI	-0.4463	0.2528	0.5319	-0.0795	0.0757	0.1102	0.127
	0.000***	0.013**	0.000***	0.4415	0.4637	0.2852	0.2175
CDSIRFMaxSV	-0.4795	0.2241	0.5094	-0.0855	0.1106	0.0265	0.0632
	0.000***	0.028**	0.000***	0.4077	0.2832	0.7979	0.541
CDSIRFPrdSI	0.0689	-0.0699	0.0027	0.0849	-0.0067	0.0897	0.0696
	0.5047	0.4984	0.9795	0.4107	0.9484	0.3849	0.5002
CDSIRFPrdSV	-0.1633	0.1782	0.0303	-0.0798	0.1741	-0.056	-0.0192
	0.1119	0.082*	0.7697	0.4395	0.090*	0.5877	0.853
EqtIRFMaxSI	-0.3492	0.2367	0.565	-0.0922	0.1048	0.1827	0.2879
	0.001***	0.020**	0.000***	0.3717	0.3097	0.075*	0.004***
EqtIRFMaxSV	-0.2939	0.1466	0.5165	0.1365	-0.1053	-0.1624	-0.0267
	0.004***	0.1542	0.000***	0.1849	0.3071	0.1138	0.7963
EqtIRFPrdSI	0.0152	0.0025	0.0024	-0.0198	0.1736	0.1362	0.0727
	0.883	0.9804	0.9816	0.8485	0.091*	0.1859	0.4816
EqtIRFPrdSV	-0.0481	-0.0668	0.1186	-0.0281	0.1002	-0.1047	**-0.1362**

	0.6415	0.5176	0.2498	0.7859	0.3311	0.3102	0.1858
CDSGrangerSI	-0.2204	0.2421	0.4653	0.0052	0.155	-0.0224	0.0859
	0.031**	0.018**	0.000***	0.9599	0.1317	0.8286	0.4054
CDSGrangerSV	-0.414	0.1497	0.3767	-0.0786	0.0094	**-0.0374**	-0.0438
	0.000***	0.1454	0.000***	0.4464	0.9273	0.7172	0.6719
EqtGrangerSI	-0.2262	0.3386	0.408	-0.1666	0.3397	0.4275	0.4662
	0.027**	0.001***	0.000***	0.1048	0.001***	0.000***	0.000***
EqtGrangerSV	0.0599	-0.138	-0.1934	0.2655	-0.2274	**-0.4367**	-0.436
	0.5622	0.18	0.059*	0.009***	0.026**	0.000***	0.000***
DiDeSI	-0.1486	0.1827	0.3096	0.4453	-0.0069	-0.3918	-0.3296
	0.1484	0.075*	0.002***	0.000***	0.9465	0.000***	0.001***
DiDeSV	-0.4278	-0.1278	0.3294	-0.411	0.1068	**0.1328**	**0.0754**
	0.000***	0.2148	0.001***	0.000***	0.3003	0.1971	0.465
LRMES	-0.516	0.3048	0.678	-0.1936	0.0835	**0.5959**	**0.7202**
	0.000***	0.003***	0.000***	0.059*	0.4186	0.000***	0.000***
SRISK	-0.6563	0.271	0.9079	-0.3952	0.2832	0.4039	0.4182
	0.000***	0.008***	0.000***	0.000***	0.005***	0.000***	0.000***

(continued)

	ES	Beta	CDSs	Z-Score	$\Delta CoRisk$SI	$\Delta CoRisk$SV	$\Delta CoVaR$SI
ES	1						
Beta	0.578	1					
	0.000***						
CDSs	0.2567	0.1326	1				
	0.012**	0.1977					
Z-Score	-0.2324	-0.2229	-0.3261	1			
	0.023**	0.029**	0.001***				
$\Delta CoRisk$SI	-0.1778	-0.1532	-0.4081	0.35	1		
	0.083*	0.1362	0.000***	0.001***			
$\Delta CoRisk$SV	**0.0626**	**0.1198**	-0.3446	0.1866	0.1268	1	
	0.5444	0.2452	0.001***	0.069*	0.2184		
$\Delta CoVaR$SI	0.3009	0.5527	-0.1309	-0.1416	-0.066	0.3754	1
	0.003***	0.000***	0.2038	0.1686	0.523	0.000***	
$\Delta CoVaR$SV	**0.6291**	**0.7349**	-0.029	**-0.2143**	-0.102	0.3144	0.7823
	0.000***	0.000***	0.7791	0.036**	0.3225	0.002***	0.000***
CDSIRFMaxSI	0.0809	0.2744	0.095	-0.2022	-0.377	0.0904	0.4716
	0.4335	0.007***	0.3573	0.048**	0.000***	0.3813	0.000***
CDSIRFMaxSV	0.0339	0.2624	0.0637	**-0.2388**	-0.465	0.0841	0.4193
	0.743	0.010***	0.5373	0.019**	0.000***	0.415	0.000***
CDSIRFPrdSI	0.1032	-0.0471	-0.3256	0.0878	0.3071	0.1258	-0.1094
	0.3171	0.6489	0.001***	0.3949	0.002***	0.2221	0.2885
CDSIRFPrdSV	-0.0627	**0.189**	-0.1459	**0.0153**	0.1609	-0.0094	0.0516
	0.5437	0.065*	0.1561	0.882	0.1174	0.9272	0.6176
EqtIRFMaxSI	0.1848	0.3769	-0.2158	-0.2819	0.0108	0.2881	0.5636
	0.071*	0.000***	0.035**	0.005***	0.9171	0.004***	0.000***
EqtIRFMaxSV	-0.0899	0.358	**-0.3089**	-0.0603	0.0732	0.2734	0.5157
	0.3838	0.000***	0.002***	0.5593	0.4785	0.007***	0.000***
EqtIRFPrdSI	0.0825	-0.1803	-0.0441	0.0162	-0.0206	0.0597	-0.0558
	0.4243	0.079*	0.6698	0.8754	0.8418	0.5632	0.5894
EqtIRFPrdSV	**-0.1313**	**-0.1869**	**0.0561**	**0.0308**	-0.0731	0.0492	-0.0268
	0.2022	0.068*	0.5871	0.7655	0.4788	0.6343	0.7952
CDSGrangerSI	0.0009	0.1256	-0.3628	-0.0626	0.007	0.1313	0.2887
	0.9932	0.2226	0.000***	0.5446	0.9458	0.2023	0.004***
CDSGrangerSV	**-0.0295**	**0.2011**	0.2376	**-0.2941**	-0.4397	-0.0262	0.2499
	0.7756	0.049**	0.020**	0.004***	0.000***	0.8003	0.014**
EqtGrangerSI	0.4033	0.0687	-0.1786	0.0134	0.0639	0.3021	0.384
	0.000***	0.5059	0.082*	0.8966	0.5361	0.003***	0.000***
EqtGrangerSV	**-0.4227**	0.0069	0.0354	**0.0329**	0.0204	-0.1724	-0.1544
	0.000***	0.9471	0.7318	0.7506	0.8439	0.093*	0.1331
DiDeSI	-0.3124	0.1175	-0.465	0.1038	0.3919	0.4047	0.2736
	0.002***	0.2541	0.000***	0.3141	0.000***	0.000***	0.007***
DiDeSV	**0.1087**	**0.3663**	**0.6589**	**-0.408**	-0.4846	-0.1828	0.1949
	0.2919	0.000***	0.000***	0.000***	0.000***	0.075*	0.057*
LRMES	**0.6248**	**0.7971**	-0.0158	-0.1905	-0.1182	0.3531	0.7223
	0.000***	0.000***	0.8785	0.063*	0.2513	0.000***	0.000***

SRISK	**0.4266**	0.479	0.0287	-0.292	-0.1524	0.3046	0.6529
	0.000***	0.000***	0.7816	0.004***	0.1381	0.003***	0.000***

(continued)

	$\Delta CoVaR$SV	CDSIRFMaxSI	CDSIRFMaxSV	CDSIRFPrdSI	CDSIRFPrdSV	EqtIRFMaxSI	EqtIRFMaxSV
$\Delta CoVaR$SV	1						
CDSIRFMaxSI	0.4008	1					
	0.000***						
CDSIRFMaxSV	0.334	0.7112	1				
	0.001***	0.000***					
CDSIRFPrdSI	-0.0237	-0.278	-0.3543	1			
	0.8185	0.006***	0.000***				
CDSIRFPrdSV	0.076	-0.0418	0.0777	0.1946	1		
	0.4619	0.6862	0.4515	0.057*			
EqtIRFMaxSI	0.535	0.3028	0.2786	0.1353	0.0694	1	
	0.000***	0.003***	0.006***	0.1888	0.5017		
EqtIRFMaxSV	0.3924	0.416	0.4524	-0.0512	0.1233	0.5018	1
	0.000***	0.000***	0.000***	0.6201	0.2314	0.000***	
EqtIRFPrdSI	-0.0731	0.101	0.0497	-0.0011	-0.0383	0.0249	-0.1099
	0.479	0.3274	0.6303	0.9918	0.7111	0.8097	0.2864
EqtIRFPrdSV	-0.0862	0.1247	0.0408	0.006	0.0575	-0.0058	0.0737
	0.4039	0.226	0.6928	0.9536	0.5779	0.9553	0.4756
CDSGrangerSI	0.2684	0.3306	0.269	0.2708	0.0834	0.3805	0.342
	0.008***	0.001***	0.008***	0.008***	0.419	0.000***	0.001***
CDSGrangerSV	0.1793	0.6148	0.7805	-0.3068	0.0991	0.2047	0.3357
	0.081*	0.000***	0.000***	0.002***	0.3366	0.045**	0.001***
EqtGrangerSI	0.4263	0.1386	0.0342	0.128	-0.1696	0.3758	-0.0217
	0.000***	0.178	0.7406	0.214	0.099*	0.000***	0.8341
EqtGrangerSV	-0.3301	-0.0179	0.0695	-0.1865	0.2142	-0.1183	0.295
	0.001***	0.8622	0.5008	0.069*	0.036**	0.251	0.004***
DiDeSI	0.15	0.1036	0.1684	0.2158	0.2063	0.3103	0.5472
	0.1445	0.3151	0.1009	0.035**	0.044**	0.002***	0.000***
DiDeSV	0.2215	0.3714	0.4528	-0.2501	0.0048	0.1604	0.2382
	0.030**	0.000***	0.000***	0.014**	0.9633	0.1186	0.020**
LRMES	0.8926	0.3106	0.3395	0.0199	0.0992	0.5928	0.4231
	0.000***	0.002***	0.001***	0.8476	0.3363	0.000***	0.000***
SRISK	0.7059	0.5025	0.5066	0.0269	0.0727	0.5392	0.4565
	0.000***	0.000***	0.000***	0.7946	0.4814	0.000***	0.000***

(continued)

	EqtIRFPrdSI	EqtIRFPrdSV	CDSGrangerSI	CDSGrangerSV	EqtGrangerSI	EqtGrangerSV	DiDeSI
EqtIRFPrdSI	1						
EqtIRFPrdSV	0.1445	1					
	0.1603						
CDSGrangerSI	0.1121	-0.0079	1				
	0.2768	0.9388					
CDSGrangerSV	-0.0672	0.0665	0.1497	1			
	0.5153	0.5197	0.1455				
EqtGrangerSI	0.4478	-0.0412	0.2978	-0.1698	1		
	0.000***	0.6899	0.003***	0.098*			
EqtGrangerSV	-0.3571	0.0021	-0.1088	0.1183	-0.6835	1	
	0.000***	0.9838	0.2912	0.2508	0.000***		
DiDeSI	-0.1248	0.1392	0.3233	0.0457	-0.0854	0.2273	1
	0.2258	0.1763	0.001***	0.6586	0.4081	0.026**	
DiDeSV	-0.167	0.12	-0.0369	0.4973	-0.265	0.1851	-0.0365
	0.1039	0.2442	0.7213	0.000***	0.009***	0.071*	0.7238
LRMES	-0.0568	-0.107	0.3343	0.2087	0.4014	-0.2515	0.2084
	0.5823	0.2995	0.001***	0.041**	0.000***	0.013**	0.042**
SRISK	0.0288	0.0567	0.3838	0.3474	0.4217	-0.2668	0.2579
	0.7806	0.583	0.000***	0.001***	0.000***	0.009***	0.011**

(continued)

	DiDeSV	LRMES	SRISK
DiDeSV	1		
LRMES	0.2502	1	
	0.014**		
SRISK	0.3899	0.7029	1
	0.000***	0.000***	

MinEqtRet (MaxCDSRet) denotes the actual minimum equity returns (maximum CDS returns) during the period from 2007 Q3 to 2008 Q4. Risk measures are their maximum or minimum values during the period of 2006 Q1 to 2007Q2. VaR is the 95th percentile. CDSs is the CDS spread. the suffix of "SI" of the systemic risk measures means the systemic importance of the firms. the suffix of "SV" of the systemic risk measures means the systemic vulnerability of the firms. "~IRFMax~" refers to the IRF results based on the maximum values of the impulse response plots. "~IRFPrd~" refers to the IRF results based on the lasting periods in the impulse response plots. ***, **, and * indicate significance at 1%,5%, and 10% respectively.

Appendix 96 Rank Correlation Matrix of the Mean Values of the Variables

	MeanEqtRet	MeanCDSRet	MeanLeverage	Size	Illiquidity	Volatility	VaR
MeanEqtRet	1						
MeanCDSRet	-0.5421	1					
	0.000***						
MeanLeverage	-0.6124	0.451	1				
	0.000***	0.000***					
MeanMV	0.2189	-0.0417	-0.2319	1			
	0.032**	0.6865	0.023**				
Illiquidity	-0.4851	0.4666	0.2787	-0.2846	1		
	0.000***	0.000***	0.006***	0.005***			
Volatility	-0.2343	0.1157	0.2889	-0.4583	0.0811	1	
	0.022**	0.2618	0.004***	0.000***	0.4323		
VaR	-0.2291	0.1404	0.3054	-0.4203	0.0119	0.9426	1
	0.025**	0.1726	0.003***	0.000***	0.9081	0.000***	
ES	-0.2691	0.1034	0.2868	-0.4058	0.0719	0.9449	0.8916
	0.008	0.3159	0.0046	0	0.4862	0	0
Beta	-0.4867	0.2056	0.5776	-0.1743	0.0172	0.5369	0.5731
	0.000***	0.044**	0.000***	0.089*	0.8677	0.000***	0.000***
CDSs	-0.059	-0.2705	-0.0308	-0.5813	0.0363	0.2953	0.2408
	0.5682	0.008***	0.7656	0.000***	0.7258	0.004***	0.018**
Z-Score	0.2444	-0.0997	-0.3667	0.2718	-0.0168	-0.221	-0.2393
	0.016**	0.3338	0.000***	0.007***	0.8711	0.030**	0.019**
$\Delta CoRisk$SI	0.0637	0.0184	0.0109	0.3849	-0.0449	-0.1484	-0.0964
	0.5372	0.8589	0.9157	0.000***	0.6641	0.149	0.35
$\Delta CoRisk$SV	-0.4027	0.6901	0.5776	0.0799	0.2728	0.1316	0.1505
	0.000***	0.000***	0.000***	0.439	0.007***	0.2013	0.1432
$\Delta CoVaR$SI	-0.4055	0.1886	0.6036	0.0698	-0.0451	-0.0028	0.1494
	0.000***	0.066*	0.000***	0.4991	0.6628	0.9788	0.1462
$\Delta CoVaR$SV	-0.4578	0.1643	0.6509	-0.1869	-0.0077	0.4681	**0.5071**
	0.000***	0.1098	0.000***	0.068*	0.9409	0.000***	0.000***
CDSIRFMaxSI	-0.5104	0.3029	0.523	-0.0874	0.1214	0.0969	0.1131
	0.000***	0.003***	0.000***	0.3974	0.2388	0.3479	0.2726
CDSIRFMaxSV	-0.4963	0.4167	0.6273	-0.0883	0.1671	0.0904	0.1362
	0.000***	0.000***	0.000***	0.3922	0.1037	0.3811	0.1859
CDSIRFPrdSI	0.1379	-0.0666	-0.1316	0.0083	0.0164	0.0045	0.0171
	0.1802	0.5194	0.2012	0.9364	0.8741	0.965	0.8683
CDSIRFPrdSV	0.0196	0.1427	-0.0378	0.0914	0.1397	-0.0488	-0.0182
	0.8497	0.1656	0.7144	0.3759	0.1746	0.6368	0.8601
EqtIRFMaxSI	-0.3923	0.2022	0.5264	-0.1034	0.1311	0.2177	0.2561
	0.000***	0.048**	0.000***	0.3162	0.2028	0.033**	0.012**
EqtIRFMaxSV	-0.2441	0.0817	0.482	0.1408	-0.0655	-0.1864	-0.1136
	0.017**	0.4285	0.000***	0.1712	0.5259	0.069*	0.2704
EqtIRFPrdSI	0.2995	-0.1764	-0.3427	0.1527	-0.0913	-0.2298	-0.2001
	0.003***	0.086*	0.001***	0.1375	0.3764	0.024**	0.051*

EqtIRFPrdSV	-0.0408	0.1507	0.169	-0.1502	0.2301	0.0425	0.0763
	0.693	0.1427	0.100*	0.1442	0.024**	0.6813	0.46
CDSGrangerSI	-0.1451	0.3026	0.4681	-0.0072	0.155	0.0416	0.0859
	0.1585	0.003***	0.000***	0.9442	0.1317	0.6876	0.4054
CDSGrangerSV	-0.4019	0.2004	0.3731	-0.0809	0.0094	-0.0251	-0.0438
	0.000***	0.050*	0.000***	0.4332	0.9273	0.8082	0.6719
EqtGrangerSI	-0.2576	0.4213	0.4107	-0.1745	0.3397	0.4124	0.4662
	0.011**	0.000***	0.000***	0.089*	0.001***	0.000***	0.000***
EqtGrangerSV	0.0807	-0.2152	-0.1887	0.2716	-0.2274	-0.43	-0.436
	0.4346	0.035**	0.066*	0.007***	0.026**	0.000***	0.000***
DiDeSI	-0.175	0.2276	0.3498	0.4325	0.0106	-0.3631	-0.3226
	0.088*	0.026**	0.001***	0.000***	0.9183	0.000***	0.001***
DiDeSV	-0.3485	-0.1453	0.3601	-0.4034	0.0861	0.1113	0.1073
	0.001***	0.1578	0.000***	0.000***	0.4041	0.2803	0.2979
LRMES	-0.4597	0.3062	0.6757	-0.1987	0.0835	0.6639	**0.7202**
	0.000***	0.002***	0.000***	0.052*	0.4186	0.000***	0.000***
SRISK	-0.6039	0.3257	0.9068	-0.3987	0.2832	0.419	0.4182
	0.000***	0.001***	0.000***	0.000***	0.005***	0.000***	0.000***

(continued)

	ES	Beta	CDSs	Z-Score	$\Delta CoRisk$SI	$\Delta CoRisk$SV	$\Delta CoVaR$SI
ES	1						
Beta	0.5113	1					
	0.000***						
CDSs	0.2618	0.0963	1				
	0.010**	0.3507					
Z-Score	-0.213	-0.3796	-0.1575	1			
	0.037**	0.000***	0.1255				
$\Delta CoRisk$SI	-0.1328	0.0212	-0.6179	0.1779	1		
	0.1972	0.8373	0.000***	0.083*			
$\Delta CoRisk$SV	0.1095	0.3154	-0.3388	-0.1583	0.0432	1	
	0.2884	0.002***	0.001***	0.1234	0.6759		
$\Delta CoVaR$SI	0.0044	0.6757	-0.2178	-0.3459	0.2091	0.3365	1
	0.9664	0.000***	0.033**	0.001***	0.041**	0.001***	
$\Delta CoVaR$SV	0.4594	0.893	0.0188	-0.4444	0.0488	0.3114	0.8073
	0.000***	0.000***	0.856	0.000***	0.6365	0.002***	0.000***
CDSIRFMaxSI	0.057	0.3852	0.1494	-0.331	-0.2763	0.31	0.4015
	0.5814	0.000***	0.1463	0.001***	0.006***	0.002***	0.000***
CDSIRFMaxSV	0.089	0.4464	-0.0526	-0.3427	-0.1859	0.3959	0.5376
	0.3883	0.000***	0.6105	0.001***	0.070*	0.000***	0.000***
CDSIRFPrdSI	0.0525	-0.138	-0.2871	0.0805	0.465	-0.1191	-0.0924
	0.6117	0.1798	0.005***	0.4358	0.000***	0.2477	0.3708
CDSIRFPrdSV	-0.0222	-0.0091	-0.4062	0.0603	0.5931	0.0641	0.0571
	0.8299	0.9295	0.000***	0.5594	0.000***	0.5352	0.5808
EqtIRFMaxSI	0.1801	0.5654	-0.0534	-0.4161	0.0905	0.3823	0.6537
	0.079*	0.000***	0.6052	0.000***	0.3807	0.000***	0.000***
EqtIRFMaxSV	-0.187	0.506	-0.1871	-0.1904	0.1163	0.2282	0.7805
	0.068*	0.000***	0.068*	0.063*	0.2592	0.025**	0.000***
EqtIRFPrdSI	-0.185	-0.2965	0.0314	0.1806	-0.0218	-0.2274	-0.2591
	0.071*	0.003***	0.7612	0.078*	0.8332	0.026**	0.011**
EqtIRFPrdSV	0.0654	-0.1776	0.0079	-0.0314	-0.1255	0.1503	-0.1062
	0.5266	0.083*	0.9388	0.7617	0.2231	0.1437	0.3032
CDSGrangerSI	0.0009	0.2574	-0.3426	-0.1822	0.219	0.4354	0.4318
	0.9932	0.011**	0.001***	0.076*	0.032**	0.000***	0.000***
CDSGrangerSV	-0.0295	0.2845	0.2715	-0.2741	-0.3943	0.1298	0.3436
	0.7756	0.005***	0.008***	0.007***	0.000***	0.2074	0.001***
EqtGrangerSI	0.4033	0.1239	-0.1897	-0.0686	0.1635	0.4133	0.1011
	0.000***	0.229	0.064*	0.5069	0.1115	0.000***	0.3268
EqtGrangerSV	-0.4527	0.0214	0.0425	-0.0482	-0.0244	-0.2103	0.0843
	0.000***	0.8359	0.6812	0.6407	0.8135	0.040**	0.4139
DiDeSI	-0.3251	0.2828	-0.6646	-0.1373	0.4511	0.3607	0.5783
	0.001***	0.005***	0.000***	0.1822	0.000***	0.000***	0.000***
DiDeSV	0.1206	0.4981	0.6515	-0.3627	-0.3996	-0.0638	0.4111

	0.242	0.000***	0.000***	0.000***	0.000***	0.5367	0.000***
LRMES	**0.6248**	**0.8904**	0.0154	-0.3107	0.0782	0.41	0.6346
	0.000***	0.000***	0.8817	0.002***	0.4487	0.000***	0.000***
SRISK	**0.4266**	**0.6357**	0.0539	-0.421	0.0222	0.4565	0.5701
	0.000***	0.000***	0.602	0.000***	0.8298	0.000***	0.000***

(continued)

	$\Delta CoVaR$SV	CDSIRFMaxSI	CDSIRFMaxSV	CDSIRFPrdSI	CDSIRFPrdSV	EqtIRFMaxSI	EqtIRFMaxSV
$\Delta CoVaR$SV	1						
CDSIRFMaxSI	0.4268	1					
	0.000***						
CDSIRFMaxSV	0.5247	0.6942	1				
	0.000***	0.000***					
CDSIRFPrdSI	-0.1095	-0.3493	-0.3167	1			
	0.2881	0.001***	0.002***				
CDSIRFPrdSV	-0.0253	-0.3336	-0.1838	0.7628	1		
	0.8065	0.001***	0.073*	0.000***			
EqtIRFMaxSI	0.6831	0.3932	0.4825	-0.0665	0.067	1	
	0.000***	0.000***	0.000***	0.52	0.5166		
EqtIRFMaxSV	0.587	0.3343	0.491	-0.1919	-0.0114	0.5099	1
	0.000***	0.001***	0.000***	0.061*	0.9123	0.000***	
EqtIRFPrdSI	-0.3064	-0.1307	-0.2409	0.0418	0.0151	-0.2907	-0.1779
	0.002***	0.2042	0.018**	0.6862	0.8837	0.004***	0.083*
EqtIRFPrdSV	-0.1472	0.0982	0.0825	-0.0166	0.0177	0.0003	-0.1027
	0.1524	0.3411	0.4242	0.8721	0.8644	0.9977	0.3195
CDSGrangerSI	0.3697	0.2311	0.4633	-0.1063	0.102	0.2761	0.3233
	0.000***	0.024**	0.000***	0.3025	0.3229	0.007***	0.001***
CDSGrangerSV	0.3213	0.6318	0.7268	-0.45	-0.3899	0.2988	0.3476
	0.001***	0.000***	0.000***	0.000***	0.000***	0.003***	0.001***
EqtGrangerSI	0.1429	0.0852	0.14	0.097	0.1774	0.1887	-0.188
	0.1648	0.4093	0.1737	0.3471	0.084*	0.066*	0.067*
EqtGrangerSV	-0.0578	0.0515	-0.0565	-0.2159	-0.0882	-0.0588	0.4113
	0.576	0.618	0.5847	0.035**	0.393	0.5691	0.000***
DiDeSI	0.355	0.1624	0.3471	0.0814	0.2597	0.3127	0.5847
	0.000***	0.114	0.001***	0.4307	0.011**	0.002***	0.000***
DiDeSV	0.5229	0.4973	0.3444	-0.313	-0.3589	0.3821	0.371
	0.000***	0.000***	0.001***	0.002***	0.000***	0.000***	0.000***
LRMES	0.8394	0.3312	0.441	-0.0842	0.0378	0.5883	0.386
	0.000***	0.001***	0.000***	0.4148	0.7144	0.000***	0.000***
SRISK	0.6958	0.5093	0.6082	-0.0409	-0.0088	0.5088	0.4115
SRISK	0.000***	0.000***	0.000***	0.6921	0.9318	0.000***	0.000***

(continued)

	EqtIRFPrdSI	EqtIRFPrdSV	CDSGrangerSI	CDSGrangerSV	EqtGrangerSI	EqtGrangerSV	DiDeSI
EqtIRFPrdSI	1						
EqtIRFPrdSV	0.1778	1					
	0.083*						
CDSGrangerSI	-0.1925	0.0331	1				
	0.060*	0.7491					
CDSGrangerSV	-0.1647	0.0548	0.1497	1			
	0.1087	0.5958	0.1455				
EqtGrangerSI	-0.1247	0.2669	0.2978	-0.1698	1		
	0.2262	0.009***	0.003***	0.098*			
EqtGrangerSV	0.083	-0.2827	-0.1088	0.1183	-0.6835	1	
	0.4213	0.005***	0.2912	0.2508	0.000***		
DiDeSI	-0.1115	-0.0121	0.4303	0.1296	-0.1068	0.2316	1
	0.2794	0.9071	0.000***	0.2081	0.3003	0.023**	
DiDeSV	-0.1042	-0.0186	0.0197	0.5003	-0.2408	0.1755	0.0066
	0.3122	0.8572	0.8489	0.000***	0.018**	0.087*	0.9493
LRMES	-0.3483	-0.0135	0.3343	0.2087	0.4014	-0.2515	0.2249
	0.001***	0.8961	0.001***	0.041**	0.000***	0.013**	0.028**
SRISK	-0.3512	0.0994	0.3838	0.3474	0.4217	-0.2668	0.2714
	0.001***	0.3353	0.000***	0.001***	0.000***	0.009***	0.008***

(continued)

	DiDeSV	LRMES	SRISK
DiDeSV	1		
LRMES	0.3047	1	
	0.003***		
SRISK	0.4276	0.7029	1
	0.000***	0.000***	

MeanEqtRet (MeanCDSRet) denotes the actual mean equity returns (mean CDS returns) during the period from 2007 Q3 to 2008 Q4. Risk measures are their mean values during the period of 2006 Q1 to 2007Q2. VaR is the 95th percentile. CDSs is the CDS spread. the suffix of "SI" of the systemic risk measures means the systemic importance of the firms. the suffix of "SV" of the systemic risk measures means the systemic vulnerability of the firms. "~IRFMax~" refers to the IRF results based on the maximum values of the impulse response plots. "~IRFPrd~" refers to the IRF results based on the lasting periods in the impulse response plots. ***, **, and * indicate significance at 1%,5%, and 10% respectively.

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